The Chinese University of Hong Kong

IMAGE CLASSIFICATION OF SPATIALLY HETEROGENEOUS LAND USE TYPE BASED ON STRUCTURAL COMPOSITION OF SPECTRAL CLASSES

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ABSTRACT

Remote Sensing technology has been widely applied in the gathering of land use data. Nevertheless, the accuracy of land use classification using remote sensing data cannot satisfy all users. A main problem affecting the classification accuracy is that conventional per-pixel classifiers do not take into account of the diverse spectral characteristics of land use which are also known as scene noises. Many methods have thus been developed for reducing these scene noises. The main trend is that classification methods have changed from simply using per-pixel spectral data to focusing on spatial structure.

Following this trend, a new method, the Spectral Class Composition Method (SCCM), emphasizing on examining the internal structure of each land use type, is developed. The SCCM is based on the hypothesis that land use types should not simply correspond to only one spectral class, but a composition of spectral classes. Knowing the types of spectral classes and their proportion constituted in each land use type, different land use types can be identified.

From the results of training process, it can be seen that each land use type in Hong Kong is usually composed of more than one type of spectral classes. This is different from the conventional method in which one land use type only corresponds to one spectral class. In the accuracy assessment, the new method, when compared with the simple per-pixel classifier, has improved accuracy results. The difference between the kappa coefficients of the two methods is also tested and proved to be significant.

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INTRODUCTION

1.1 Background

Nowadays, human beings face problems of haphazard, uncontrolled development, deteriorating environmental quality, as well as loss of prime agricultural land, wetland, fish and wildlife habitats. In order to overcome these problems, knowledge about land use has become increasingly important. Land use data are required in the analysis of environmental processes and problems that must be understood if we want to improve living conditions and standards or maintain them at current levels (Anderson et al., 1976).

Remote sensing technology has been widely applied in the gathering of land use data because it possesses several advantages over other traditional data collection methods, such as field studies. These advantages include: i) high speed processing; ii) frequently obtained new data; iii) unbiased and uniformly repetitive classification; iv) production of print-out maps at a large map scale at relatively low costs (once the system becomes operational) and v) the inherent digitizing of land use data which can be retrieved in virtually any form or combination of forms (Ellefsen et al., 1973; Gordon, 1980).

Nevertheless, the accuracy of land use classification using remote sensing data cannot satisfy all users. This is especially true in the classification of land use types with high internal variability such as residential areas which typically comprise trees, roads, rooftops, and lawns. In Gordon's study (1980), many misclassification problems were revealed when the results of Landsat classification were compared with that of using air photos. Urban land use types were subject to greater errors. Less than 50% of the residential areas was classified correctly while the accuracy of industrial areas and commercial areas were 12% and 8% respectively. Gordon concluded that direct application and use of remote sensing data had to await improvements in classification techniques and accuracy.

A main problem affecting the accuracy of classification is the diverse spectral characteristics of land use. For digital image classification, an idealized area of land use should be spectrally homogeneous. Accurate mapping of such an area can thus be accomplished by the process of matching spectral responses to the spectral "signatures" of informational categories. However, actual land use areas often appear as assemblages of spectrally diverse features. For example, a high class residential area is composed of tree crowns, rooftops, lawns, paved streets, driveways, and parking lots. We are interested in the classification of the integrated composite of these features rather than the individual features. Thus, ideally, classification should focus upon the overall composition of these constituent features that characterize each land use type, rather than upon average brightness of these features which may not reveal much about the essential differences among categories (Campbell, 1987). Although human interpreters can intuitively recognize such complex patterns, many per-pixel based digital classification algorithms encounter serious problems in the classification of heterogeneous land use types. In these classifications, each pixel is classified into a spectral class according to the brightness values in different spectral bands. Each of the resulted classified spectral classes is assumed to be correspondent to a particular land use type. These spectral classes may not be able to reveal the true nature of land use types. Since it has not taken into account of the fact that land use types may comprise different spectral classes.

Some methods have been used to solve the problem. Using filtered data is one of the attempts to improve the accuracy of classification result. It reduces the spatial resolution and averages out the scene noise (internal variation) of each resulted class after classification (Cushnie and Atkinson, 1985). Textural classifiers attempt to measure image texture —— a description of the spatial variability of tones found within part of a scene (Haralick, 1979). Contextual classifiers attempt to measure image context —— spatial relationships with pixels in the remainder of the scene (Gurney and Townshend, 1983).

It is found that classification methods have changed from simply using per-pixel spectral data to focusing on spatial structure. Results of the latter one show salient improvement. The new method in this study is developed following this trend.

On the whole, conventional methods consider the spectrally diverse features in land use types as scene noises. which is believed to have adverse effect on the accuracy of classification. Various methods are thus devised to eliminate these scene noises. In this study, it is however thought that these spectrally diverse features are the major characteristics of different land use types. In other words, each land use type should not simply correspond to only one spectral class, but a composition of spectral classes. For instance, a high class residential area is composed of water bodies, roofs, vegetation and roads etc. which are all spectrally diverse features. Based on the composition these spectral classes and their proportion constituted in a land use type, different land use types should be identified.

1.2 Objectives

This thesis, emphasizing on the internal structure of land use, attempts to prove that the composition of spectral classes can be the visible evidence for land use classification. Based on this concept, the Spectral

Class Composition Method (SCCM) is developed as a trial to increase land use classification accuracy.

The objectives of this thesis are:

(a) To study the composition of spectral classes within each land use type in Hong Kong;

(b) To develop a new classification method based on the information acquired in (a); and

(c) To test the accuracy of the new method.

1.3 Hypotheses

Under the above objectives, two hypotheses are raised:

(a) Land use types are composed of more than one spectral classes.

(b) The new classification method —— Spectral Classes Composition Method (SCCM) —— developed according to the above relationship can increase land use classification accuracy.

1.4 Organization of the Thesis

This thesis is organized in six chapters. Besides this introductory chapter, techniques of applying remote sensing in land use classification are reviewed in chapter 2.

Chapter 3 describes the concept and the procedures of the Spectral Class Composition Method as well as the research design.

Chapter 4 mainly focuses on using training process to analyze the spectral class composition of the land use types. The hypothesis that one land use type usually consists of more than one spectral class is tested.

Chapter 5 analyzes the classification and accuracy assessment results of different types of SCCM and their comparison with simple per-pixel classification results.

Chapter 6 is the concluding chapter.

CHAPTER 2
LITERATURE REVIEW

2.1 Land Use and Land Cover

2.2 Information Classes and Spectral Classes

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2.7 Contextual Classifier

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2.10 Concluding Remarks

This chapter introduces the concept of applying remotely sensed data in land use classification. It further discusses the problem faced by conventional classification methods especially in the trend of increasing spatial resolution of remote sensors. The methods developed for solving the problem are also reviewed.

2.1 Land Use and Land Cover

Land use can be defined as human activities on land which are directly related to the land (Clawson and Stewart, 1965). Land use is not directly observable even by the closest inspection. It forms an abstraction, that is, we cannot see the actual use of a parcel of land but only the physical artifacts of that use (Campbell, 1987). In contrast, land cover only describes the vegetational and artificial constructions covering the land surface (Burley, 1961). In a much broader sense, land cover designates the visible evidence of land use, including both the vegetative and the non-vegetative features. In this sense, dense forest, plowed land, urban structures and paved parking lots all constitute land cover. While land use is abstract, land cover is concrete and is, therefore, subject to direct observations (Campbell, 1987).

In remote sensing classification, it is difficult to record activity directly. Remote sensors acquire responses which are based on spectral characteristics of the land surface. The interpreter then uses pattern, tone, texture, shape, site and association to derive information about land cover from which land use activities can be further deduced (Anderson, Hardy, Roach, Witmer, 1977).

Some land use types, however, cannot be directly related to the type of land cover. For example, hunting usually occurs on land that would be classified as some type of forest, range, or agricultural land during image interpretation. For this reason, the types of land use and land cover identifiable primarily from remote sensor data are used as the basis for organizing the classification scheme (Anderson, et al., 1977). Thus, land use and land cover are usually invariably used in association in remote sensing classification (Rhind and Hudson, 1980).

2.2 Informational Classes and Spectral Classes

Informational classes are the categories of interest to the users of remotely sensed data. Informational classes are, for instance, the different kinds of geological units, forest or land use that convey information to planners, managers, administrators and scientists. These classes, or the output of the analysis, form the information that we wish to derive from the data. However, these classes are not directly recorded on remotely sensed images. We can only derive them indirectly by using evidences contained in the brightness recorded on each image (Campbell,1987).

Spectral classes are groups of pixels that are uniform with respect to the brightness in several spectral channels. They can be observed within remotely sensed data. If it is possible to define links between the spectral classes on the image and the information classes that are of primary interest, a valuable source of information can be formed. By matching spectral categories to informational categories, remote sensing classification becomes meaningful (Campbell,1987).

2.3 Simple Per-Pixel Classification Method

Digital image classification is the process of assigning pixels to meaningful classes. Usually each pixel is treated as an individual unit composed of values in several spectral bands. By comparing pixels to one another and to pixels of known identity, it is possible to assemble groups of similar pixels into classes that match the informational categories of interest. These classes are assumed to be homogeneous —— pixels within classes are more similar to one another than they are to pixels in other classes. The simplest form of digital image classification is to consider each pixel individually, assigning it to a class based upon its multi-spectral values. Such a classifier is referred to as spectral, or per-pixel classifier because it considers each pixel as a "point" observation (in other words, as values isolated from their neighbors). Although per-pixel classifier offers the benefits of simplicity and economy, it is not capable of exploiting information containing relationships between each pixel and its neighbors

(Campbell, 1987).

The process of multi-spectral classification may be performed using either supervised or unsupervised methods. In a supervised classification, through a combination of field work, analysis of aerial photography, maps and personal experience, the identity and location of some of the land use types such as urban, agriculture, wetland and forest can be distinguished (Heaslip, 1975). Analysts attempt to locate specific sites in the remotely sensed data that represent homogeneous examples of these known land use types (Townshend, 1981). These sites are usually regarded as training sites because their spectral characteristics are used to "train" the classification algorithm for eventual land use mapping of the remainder of the image. Multi-variate statistical parameters (means, standard deviations, covariance matrices, correlation matrices, etc.) are calculated for each training site. Every pixel, both within and outside these training sites is then evaluated and assigned to the class of which it has the highest likelihood of being a member.

In an unsupervised classification, the identities of land use types to be specified as classes within a scene are not generally known a priori as there may be a lack of ground truth or surface features within the scene that are not well defined. Pixel data are grouped or clustered into different spectral classes by computers according to some statistically determined criteria. These clusters are then labeled by the analysts.

2.4 Scene Noise and Boundary Effect

Landsat-4 and Landsat-5 were successfully launched in 1982 and 1984 respectively with enhanced remote sensing capabilities for use in assessing land resources. There are two sensors on board: one is the Multi-spectral Scanner (MSS) which is similar to the MSS on board Landsats 1-3 and the other is the Thematic Mapper(TM), which is an improved sensor over Landsat MSS. Primary sensor improvements in TM over MSS include increased sensor radiometric performance, additional and refined spectral bands, and increased spatial resolution (Toll,1985).

With the launch of the French satellite SPOT in 1986, satellite remote sensing data became available at higher spatial resolutions (i.e., 20*20m and 10*10m in the multi-spectral and panchromatic modes respectively). The level of detail presented in the images has increased.

The use of higher spatial resolution data is expected to yield increased accuracy of land use identification in comparison with the lower resolution data (Salomonson et al., 1980). However, according to

Wiersma and Landgrebe (1978), increasing resolution might lead to a lower classification accuracy due to the spectral heterogeneity of land use types, or "scene noise". Scene noise tends to be averaged out at lower spatial resolution. This averaging process results in a reduction in the size of the spectral space for any given cover class. This means that there is less overlap with other cover classes, resulting in higher classification accuracy as compared to those based on higher resolution data (Markham and Townshend, 1981). For example, in an area of woodland , higher resolution data may enable the classifier to distinguish between brightly lit crowns, part of crowns in shadow, and gaps in the woodland and so on, each with a separate spectral response and hence likely to be assigned to different classes if a simple per-pixel classifier is used (Atkinson et al., 1985). To improve the accuracy, a change in standard methods used to classify the scene is need.

Besides scene noise, boundary (mixed) pixels can affect classification accuracy. This factor is boundary (mixed) pixels. When the spatial resolution is reduced, more boundaries occur. These boundary pixels contain a mixed response from two or more land cover classes. These pixels may be classified into one of these classes, or they may be classified as some other classes not contained within their boundaries. The increasing percentage of boundary pixels at coarser resolutions tend to decrease classification accuracy (Markham and Townshend, 1981).

2.5 Using Filtered Data

The problem of multi-spectral image classification in remote sensing has been approached through spectral features derived from each channel. However, the task of discrimination is sometimes difficult and the inclusion of textural attributes can be helpful. Texture is a description of the spatial variability of tones found within part of a scene. If one is interested in pixel classification, local textural properties seem to be useful. These local features can be extracted by filtering, since the spatial frequency content expresses, the spatial relationships between pixels. (Dutra, Mascarenhas, 1984)

Many studies aimed at improving the accuracy of classification. Some of them are concerned with reducing the scene noise effects within land use categories where this is necessary, without significantly increasing the proportion of boundary pixels between the categories. Methods of reducing scene noise include that of applying mean filter to the original imagery prior to per-point classification. Under this operation, scene detail is smoothed and the gray level range is reduced. But there is an increase in pixels with responses from more than one land use category as the boundaries in the image are blurred. An alternative method of pre-classification filtering is to smooth the imagery using median filter. This type of filter has the advantage of minimizing the loss of boundary detail while still removing scene noise effects (Cushnie and Atkinson, 1985).

Actually, there is a certain degree of inaccuracy when using mean filter as a tool. For example (Figure 2.1), the original values of two different centers are 0 and 10 which most probably represent two totally different land covers (e.g. water and vegetation respectively). Using filter, however, may hide away some facts and lead to errors (in this case , the two filtered values are identical, i.e. 4.9). This is also the case when using a median filter. It reduces spatial variation and thus the real situation of the earth surface cannot be fully revealed. The image becomes consisting of unreal homogeneities.

Filtering represents a reductionist approach in the scene. It attempts to solve the problem of higher spectral confusion by eliminating part of the information that is present in the image.

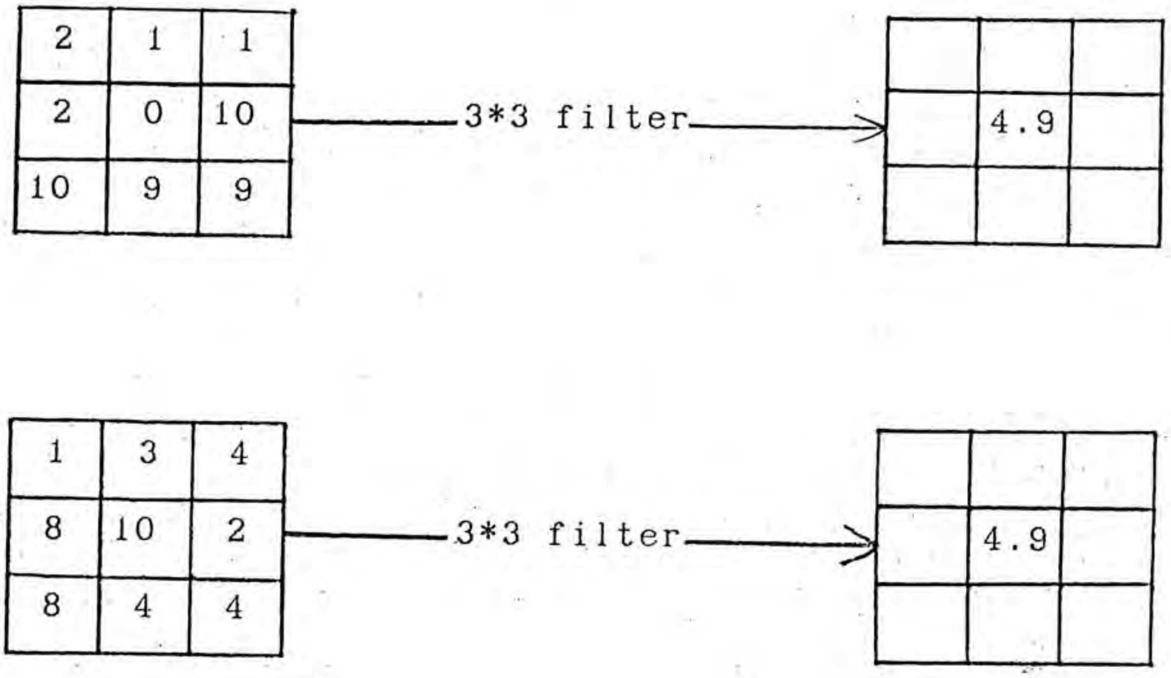

Figure 2.1 Example of Filtering

2.6 Textural Classifier

Spectral features describe the band-to-band tonal variations in a multi-band image set, whereas textural features contain information about the spatial distribution of tone values within a band (Haralick and Shanmugam, 1974). It attempts to measure distinctive spatial and spectral relationships between neighboring pixels. For example, the standard deviation of brightness values within a neighborhood of specified size, systematically moving over the entire image, may provide a rough measure of the spectral variability over short distances as a measure of image texture (Campbell,1987).

The image texture being considered is nonfigurative and cellular. Haralick (1979) treated this kind of texture as an organized area phenomenon. He felt that when it is decomposable, it has two basic dimensions on which it may be described. The first dimension is for describing the primitives out of which the image texture is composed. The second dimension is for the description of the spatial dependence or interaction between the primitives of an image texture. The first dimension is concerned with tonal primitives or local properties, and the second dimension is concerned with the spatial organization of tonal primitives.

The definition of texture is quite simple. There are, however, various methods for extracting such information. These methods can be grouped into two board categories: Fourier-based (power spectrum) features and statistical features. In a more detailed classification, according to Haralick (1979), texture analysis methods include statistical approaches of auto-correlation function, optical transforms, digital transforms, textural edgeness, structural element, gray tone co-occurrence, run lengths, and auto-regressive models.

Many scholars have attempted to apply different textural classifiers for remote sensing classification. Hsu (1978) applied his textural transformation in the analysis of low and high altitude aerial photographs. The texture analysis was divided into two models. In Model I, 17 spatial tone measures derived from a 3 by 3 data matrix, were determined as very effective in classifying general land use types. With six additional wave-form parameters, Model II was developed especially to discriminate objects and scenes of complex differences.

Similar methods were also applied by Irons and Petersen (1981). It is proved that these methods were effective in edge detection and image enhancement. However, there was no proof that it was useful as features for thematic mapping of land cover.

Jensen (1979) has empirically evaluated the utility of four measures in land cover mapping in conjunction with the Landsat spectral features. The measures are standard deviation, contrast, high frequency filter and angular second moment. It is found that the contrast and high frequency measures could improve land cover classification at the urban fringe. However, the decision to use texture measures should be weighed carefully because they yielded only a small, yet important, increment in absolute classification accuracy and data pre-processing was required.

Conners and Harlow (1980), have evaluated the ability of four texture analysis algorithms including spatial gray level dependence method (SGLDM), the gray level run length method (GLRLM), the gray level difference method (GLDM) and the power spectral method (PSM). It was found that SGLDM is the most powerful algorithm among the four and that the GLDM was more powerful than the PSM.

Hlavka (1987) has applied edge density measures in the land use mapping with Thematic Mapper simulator data. The results of classification of texture images showed that urban and rural area could be distinguished with the above texture measures. This indicated that the inclusion of texture in automated classification procedures could significantly improve their accuracies.

A method for incorporating textural information into conventional classification procedures is derived by Gong and Howarth (1990). This method is based on the use of an edge-density image which is generated by using a laplacian operator. This image is included in a Mahalanobis Classifier as an additional band of the data. In the test of identifying urban and suburban areas, the overall accuracy of this method is higher than that of the conventional ones.

However, one disadvantage of textural measures is that there is an effective reduction in spatial resolution of the final classified image because an area has to be defined within which the measurements of texture are made. This is particular disadvantageous when low resolution satellite data are used (Gurney and Townshend, 1983).

2.7 Contextual Classifier

While texture refers to the spatial variation within a group of neighboring pixels, the context of a pixel (or a group of pixels) refers to its spatial relationships with pixels in the remainder of the scene. Thus, contextual classification of any pixel involves the use of any other pixel or group of pixels throughout the whole scene. A contextual decision rule can be applied either to raw image data, in which case the spectral or textural properties of other pixels can be considered, or to classified data, in which case a preliminary classification can be amended by considering classifications assigned to other pixels. This implies not only that classification error might be reduced by using contextual information, but also that additional classes could be recognized by separating pixels with the same spectral properties into additional classes according to their context (Gurney and Townshend, 1983).

There are many kinds of method for extracting contextual information. Kettig and Landgrebe (1976) developed a technique called Extraction and Classification of Homogeneous Objects (ECHO), which segments a scene into homogeneous objects and uses sample classification to assign each object as a whole rather than by its individual pixels. Welch and Salter (1971) presented a method for the contextual classification of imagery data. Chittineni (1979) discussed the use of context with linear classifiers.

Toussaint (1978) gave a brief review of the use of context in pattern recognition and presents an extensive list of references on the subject.

Townsend (1986) created a method called a "majority filter". It is a logical rather than numerical filter since a classified image consists of labels rather than quantized counts. The simplest form of the majority filter involves the use of a filter window, usually measuring 3 rows by 3 columns, and centered on the pixel of interest. The number of pixels allocated to each of the k classes is counted. If the center pixel is not a member of the majority class (containing five or more pixels within the window), it is given the label of the majority class.

Harris (1981;1985) described a method of post-classification processing which uses a probabilistic relaxation model while Thomas (1980) reported a method based on what he called a proximity function. Wharton (1982) also developed a post-classification context algorithm to improve the results. Gurney and Townshend (1983) extracted the contextual information according to four basic forms of relationship —— distance, direction, connectivity, and containment.

Each of the contextual classifier can increase the classification accuracy at different degree. Gurney and Townshend (1983) concluded that full and successful use of higher resolution data from satellites relies on the appropriate application of classifiers with context.

2.8 Geographic Information System (GIS)

GIS is a technical system. With the support of computer hardware, this system can preprocess, input, store, examine, calculate, analyze, and update spatial data for various applications.

Substantial improvements can be made in classification accuracy if ancillary data (terrain, soils, previously determined land cover, etc.) are used in the classification process. Cleynnbreugel, Fierens, Suetens and Oosterlinck (1990) combined satellite image and GIS-guided technique to delineate road structures. They pointed out that to solve a spatial image recognition problem like the extraction of roads and linear networks from remotely sensed imagery, human analysts have to rely on their expertise in combining external data sets with spectral data (e.g. topographic maps and land cover classifications). Such data are now typically stored in GIS. For delineating road structures on satellite imagery, using these ancillary data not only can increase the accuracy, but also lighten the human effort.

Janssen, Jaarsma and Van der Linden (1990) also thought that using spectral value solely for classification is insufficient to meet the needs. They therefore attempted to add topographical data from GIS to improve the classification accuracy. Firstly, they modified a digital topographical map to serve as input for an object classification. An object has been defined as an area where only one land cover type is expected. The results of a per pixel classification were used per object to determine the land cover type of that object. This result was fed back to the GIS. The object classification improved the overall accuracy of two agricultural regions in the Netherlands by 12% and 20%.

2.9 Expert System and Artificial Intelligence (AI)

Expert systems are computer systems that advise on or help solve real-world problems which would normally require a human expert's interpretation. Such systems work through problems using a computer model of expert human reasoning. They are designed to reach the same conclusions that a human expert would be expected to reach if faces with a comparable problem (Robinson and Frank, 1987).

Expert Systems, in recent years, have been widely applied in remote sensing and GIS. It assists GIS to perform the task of map design, terrain and feature extraction, geographic database management and geographic decision support systems. It also offers possibilities for making geographic information systems more efficient and user-friendly to handle large quantities of spatial data acquired by remote sensing systems.

In remote sensing, expert systems are designed to adopt a knowledge-based classification approach. Wharton (1987) attempted to use a prototype expert system to demonstrate the feasibility of classifying multi-spectral remotely sensed data on the basis of spectral knowledge. In the testing results, the spectral expert achieved an accuracy of 80% correct or higher in recognizing 11 spectral categories with Thematic Mapper Simulator data for the Washington, DC. area.

Moller-Jensen (1990) also adopted an expert system approach which incorporates information of texture, content and reflectance characteristics to classify an urban area. Intelligent detection of roads and linear structure was first used to define image segments. For each segment, computation of features including texture, was made. An expert system approach was then used to make the final classification. Lastly, the classification procedure was tested using a Landsat-TM image covering the central parts of Bangkok. The resultant map has an acceptable accuracy in view of the spatial resolution of the data.

Artificial Intelligence (AI) may be regarded as an attempt to understand the processes of perception and reasoning that underline successful problem-solving and to incorporate the results of this research in effective computer programs. At present, AI is largely a collection sophisticated programming techniques. Many of these techniques are based on the premise that the manner in which knowledge is acquired, organized, accessed and modified in both humans and machines provides the basis of "intelligent" decision-making. The techniques of AI are applicable to a wide variety of geographical problems, including the modeling of individual and aggregate decision-making, and the construction of expert systems and "intelligent" geographic information systems (Smith, 1984).

Techniques for automating the image analysis process would be advanced by the inclusion of artificial intelligence techniques in the design of image processing systems. The remote sensing applications which show promise for successful implementation of artificial intelligence techniques are intelligent on board processing, advanced database interrogation, and the automated analysis of multi-spectral imagery (Estes, Sailer and Tinney, 1986).

Nowadays, the application of artificial intelligence in remote sensing is not popular. It will however be more widely applied in GIS.

2.10 Concluding Remarks

Simple per-pixel classifier only considers each pixel as a 'point' observation, i.e. as values isolated from their neighbors. Nowadays, satellite remote sensing data are available at higher spatial resolutions. The from their neighbors. Nowadays, satellite remote sensing data are available at higher spatial resolutions. The level of details presented in the images has increased. However, increasing resolution may lead to a lower classification accuracy when using simple per-pixel classifiers. This is because the spectral heterogeneity of land use types (or scene noise) become distinct with high spatial resolution data. The simple per-pixel method, using only spectral characteristics for land use classification, is unable to cope with the emergence of large amount of scene noise. The classification accuracy is therefore lowered.

In view of the problem, many methods have been developed for reducing the scene noise. The main trend is that classification methods have changed from simply using per-pixel data to focusing on spatial structure. These methods include textural and contextual classifiers etc. Although recently GIS and Expert System have been more widely applied as complements in land use classification , spatial structure still plays a very important role in this field.

Nowadays, many methods adopting the structural approach with a view to increasing accuracy. Nevertheless, an essential concept of land use structure has not received enough attention. This is the concept on "composition of spectral class".

Following such concept, this study does not consider that the heterogeneity of land use types, the so called scene noise, as noise. On the other hand, it places special attention on such a characteristic and test that it can be used as evidence for identifying land use.

Moreover, the conventional concept that one land use type corresponds to only one spectral class is considered incomplete. This study therefore hypothesizes that one land use type should correspond to a composition of spectral class and according to such composition, land use types can then be identified. The new method, studying the spectral class composition of different land use types is further developed.

CHAPTER 3

METHODOLOGY

3.1 Spectral Class Composition Method (SCCM)

- 3.1.1 The Concept of the Spectral Class Composition Method (SCCM)
- 3.1.2 Unsupervised Classification Process
- 3.1.3 Training Process
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- 3.1.9 Summary

3.2 Research Design

- 3.2.1 Study Area
- 3.2.2 Data and Instruments Used
- 3.2.3 Classification Scheme
- 3.2.4 Accuracy Assessment

The derivation of the concept of Spectral Class Composition Method (SCCM) is discussed in this chapter. The procedures of SCCM and the research design are also illustrated.

3.1 Spectral Class Composition Method (SCCM)

3.1.1 The Concept of the Spectral Class Composition Method (SCCM)

It was noted in chapter II that while the spatial resolution of the satellite sensors is increasing, the accuracy of per-pixel classification using these data does not necessarily increase, but often decreases. This is due to the emergence of a large amount of scene noises resulted from the increased spatial resolution.

The following example illustrates the disadvantages of the conventional per-pixel classification (Table 3.1 and Figure 3.1). A high class residential area may include the following features (all the brightness values are simplified for discussion):

(a) man-made pool with a brightness value of 0 in band i;

(b) concrete with a brightness value of 5 in band i;

(c) vegetation cover with a brightness value of 10 in band i.

Table 3.1 Brightness values in Band i of the High Class Residential Area. (an example)

Features	Spectral Band i
pool	0
concrete	5
vegetation	10

	5	10	0	
	0	5	10	
	10	0	5	

Figure 3.1 Brightness value of a High Class Residential Area (an example)

In an unsupervised classification, this high class residential area is finally classified into three different classes, namely water bodies, buildings and vegetation cover. This obviously cannot help us in understanding the actual land use.

In a supervised classification, training sites are chosen. Statistics such as mean vectors of each land use type are extracted which are in fact the average of the data values of the associated heterogeneous pixels. It is assumed that pixels belonging to the same land use type should consist of brightness values similar to those of the training sites. As a result , the average brightness value is five, representing the land cover of concrete in this example. All pixels representing concrete are then classified as high class residential land.

Cushnie and Atkinson (1985) thought that spatial variation within a certain type of land use was scene noise and attempted to remove it by filtering. This may lead to more inaccuracy. For instance, a high class residential area includes mainly water bodies, concrete and vegetation cover while a crowded low class residential area is largely composed of concrete cover (Figure 3.2). After filtering, the center pixels of both areas will have an identical value of 5.0. This result is produced with either the median or the mean filters. From this, we can see that though the two pixels belong to different land use types, they are grouped into the same class.

1. High Class Residential Area

(a) Original brightness values

0	5	10
5	10	0
10	0	5

—3*3 Mean Filter→

(b) Brightness value of center pixel after filtering

	5	

2. Low Class Residential Area

(a) Original brightness values

5	5	4
5	5	5
5	6	5

—3*3 Mean Filter→

(b) Brightness value of center pixel after filtering

	5	

Figure 3.2 Example of Using Filtering.

Scene noise which reflects the spectral heterogeneity of land use types usually reduces the degree of accuracy when simple per-pixel classification method is applied in remote sensing image classification. This is especially true as the spatial resolution of the sensors is constantly increasing nowadays. Nevertheless, if the so-called "noise" is understood more clearly and is applied appropriately, it may, on the contrary, increase the classification accuracy.

One land use type may be composed of several ground features (for example, high class residential area usually includes residential buildings, vegetation cover, streets, pools, etc.). Those ground features are represented by different spectral classes derived from any per-pixel classification. They constitute different types of land use which result in variant spectral reflectance (refer to Figure 3.3). Most of the heterogeneous land use types, therefore, consist of different spectral classes. There are, also, some land use types that may consist of a uniform spectral class.

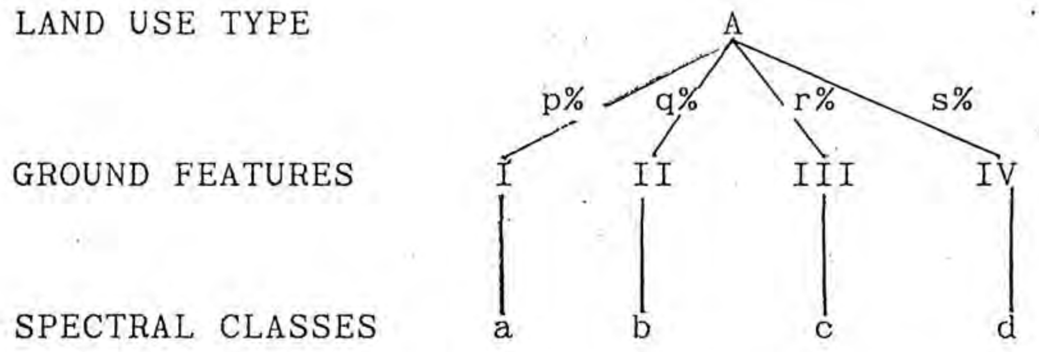


Figure 3.3 Relationship between Land Use Classes and Spectral Classes

As land use types may consist of more than one spectral class, different spectral class composition should be an essential clue for identifying land use types. For instance, a high class residential area, when compared with low class residential area, should have more open space, more vegetation covers, less tall buildings and less shadow. Another example is that commercial centers should have the highest density of buildings and more shadow resulted from the high-rise buildings. All these characteristics, in fact, can be observed in the remotely sensed data. However, there is a problem that they are usually studied in a per-pixel manner rather than in a composite one. If these data can be studied in a composite way, it is highly likely to identify the spectrally heterogeneous land use types.

Another point is that one spectral class can usually be included into more than one land use type. For example, a spectral class, bare soil, is in both the *low density residential area* and *recreational area*. This fact cannot be illustrated by the simple per pixel classifier in which one spectral class only correspond to one land use type. However, under the concept of spectral class composition, one spectral class can included into more than one land use type.

Based on the above, a new classification method —— Spectral Class Composition Method (SCCM) —— is developed. The principle underlying this method is that different land use types correspond to different composition and proportion of spectral classes. The procedures of the method are shown in Figure 3.4.

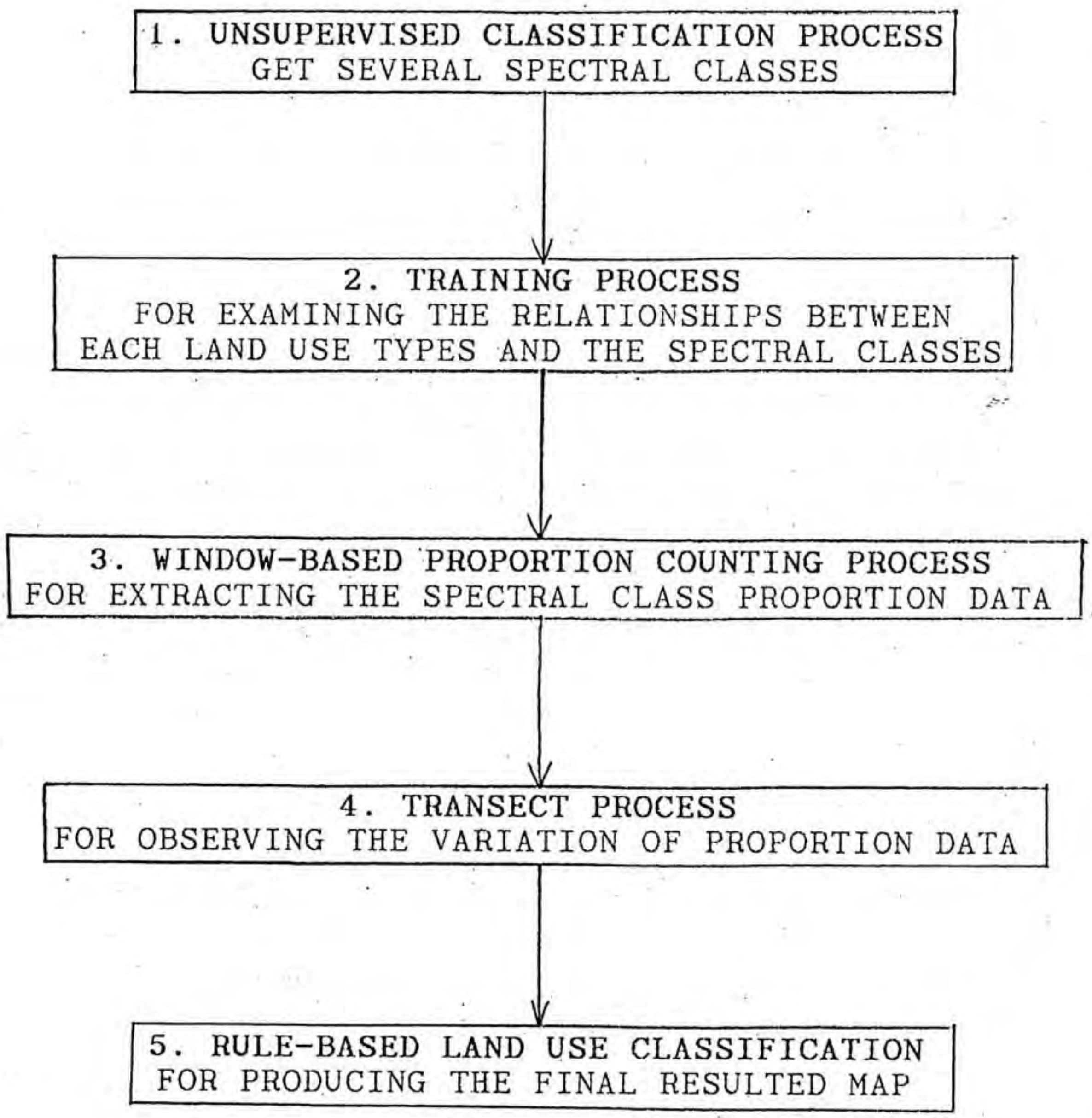


Figure 3.4 Flow Chart of the Spectral Class Composition Method

3.1.2 Unsupervised Classification Process

Firstly, remote sensing data is classified into several spectral classes using the unsupervised classification method. Unsupervised method is chosen because spectral classes with statistically significant boundaries can be classified solely according to the values of the spectral data. If supervised classification method is applied in the training process, scene noise will be easily included in the training data and errors will be resulted because training sites are spectrally heterogeneous. Unsupervised classification method can avoid these errors. After the classification, a spectral class classification map is resulted,

3.1.3 Training Process

Second, as in a supervised classification process, training sites of different land use types are drawn according to ancillary information (such as aerial photos and field study data). However, there is a difference from the traditional methods. In the traditional methods, the data extracted from the training sites are spectral statistics such as mean, variance co-variance matrix. In this method, the data extracted are the compositions of different spectral classes (identified from the spectral class map derived in the first step).

The spectral class composition extracted can be applied in identifying land use types. For instance, as illustrated in Figure 3.5, land use type I should have 20% of spectral class A, 40% of spectral class B and 40% of spectral class C. These composition data can then be regarded as land use classification "rules".

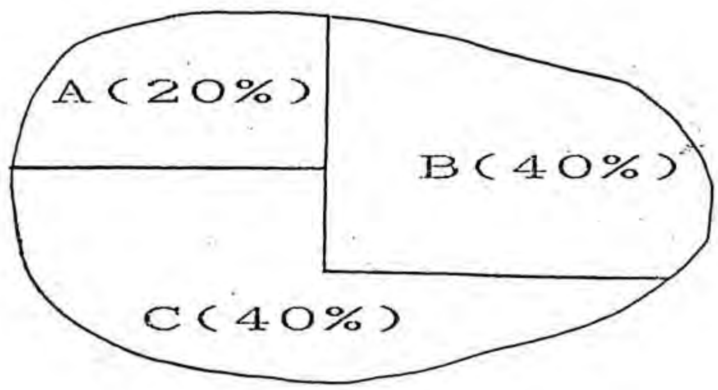


Figure 3.5 A Training Site of Land Use Type I

3.1.4 Proportion Counting

In the training process, boundaries of training areas are drawn with reference to the ancillary information. During actual classification, it is however difficult to estimate the boundaries of all the land use types. Without these boundaries, the extraction of spectral class composition data becomes impossible. A window based proportion counting method is thus used.

It is assumed, firstly, that m numbers of spectral classes are resulted from the unsupervised classification. The proportion of each spectral class in a neighborhood of n*n pixels of each center pixel is counted. The data about this spectral class proportion is then recorded in a new channel. A total of m spectral class proportional channels is then derived from one spectral class map and these channels, are used for image classification.

If one land use type does not consist of all m spectral classes, the spectral class proportion of several spectral classes will have zero values. This affects the classification result when simple statistical method is used. In addition, the commonly used parametric classifiers are based on the assumption that ground objects can be discriminated on the basis of statistical distribution of their spectral signatures. It is also assumed that each group can be enclosed by a boundary, such as defined by the hyper-ellipsoid shaped decision volume of maximum likelihood classifier. When studying the spectral class proportion data, there is no guarantee that the group has its uniform shape. As a result, it is more reasonable to use a rule-based classification method.

3.1.5 Number of Spectral Class

Before classifying the proportion data, the characteristics of these data should be well understood so that a suitable classification method can be devised.

The characteristics that must be observed are, (a) the number of spectral classes produced from unsupervised classification; (b) the window size for extracting the proportion data; and (c) the spatial variation of the proportion.

The number of proportion data channels is determined by the number of classes derived from unsupervised classification. The number of classes in turn is a determinant factor of the accuracy of the processes there follows. Fewer classes (e.g. only three classes of vegetation, water and bare soil) may lead to over-generalization of the spectral class map which is not able to characterize a particular land use.

On the contrary, if the class number is increased, the classification will become meticulous. The results from using the various types of spectral classes for training land use are also more satisfactory. Nevertheless, too many classes may result in the extreme case that the number of pixels associated with spatial classes is too small. It becomes difficult to label the spectral classes and thus is not very useful in training.

3.1.6 Window Size

The size of the window may have considerable effects on the proportion observation results. With a small window size, the proportion data obtained is limited to a small spatial area. The internal structure of land use types may therefore unable to be extracted clearly.

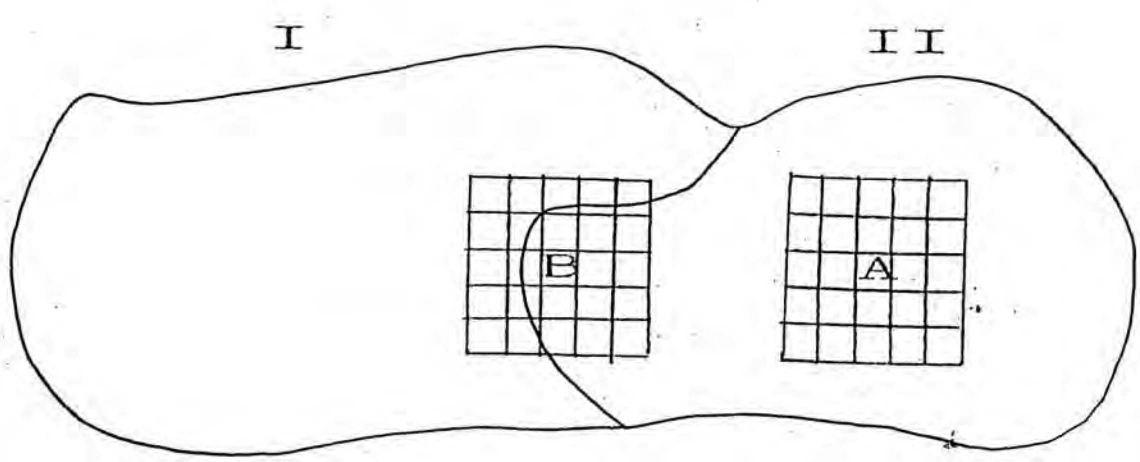
If a large window size is used, the problem of occurrence of boundary effect will arise. Spectral classes counted may not belong to particular land use type of interest. This boundary effect often has adverse effects on classification accuracy.

In fact, in different areas or land use types, the window size required may be different. To obtain the best window size, experiments should be considered.

3.1.7 Transect Process

Although window algorithm can count the spectral class proportion of the pixels within a definite area (n*n pixel), it does not guarantee that this area is specifically under a land use type. The nature of its data may be different from the composition data extracted in the training process. In order to have a clearer understanding of the proportion counting results, another training process is necessary.

There may be variations in the proportion counted within the land use type. For instance, those pixels located at the center of a land use parcel may have different proportion as compared to those located at the boundary. The window on the boundary may include the characteristics of neighboring land use types and different results are thus obtained. As illustrated in Figure 3.6, pixel A is located at the center of land use type II while pixel B is near the boundary. If a 5*5 window is set to count the spectral class proportion, it can be seen that the proportion counted in A is completely within land use type II. Those counted in B however include a large portion of land use type I. To avoid such a problem, the transect process is used. This is to extract training data from a transect which lies within representative areas of a land use type. Through this process, the variation of spectral class proportion data from the central point to the boundary can be known. The extent of variation for each land use type can also be derived. These information are then used to amend the "rules" derived from the training process.



I & II are two types of land use.
A & B are two pixels.

Figure 3.6 Proportion Counting at Different Positions of Land Use Blocks

3.1.8 Classification Task

The classification work is mainly focused on the compilation of classification rules.

The information extracted from the training process is the total composition of spectral classes constituted in the training sites. From the proportion counting process, the spectral class proportion in the surrounding window (n*n pixels) of a pixel is obtained. In the transect process, the spatial variation of the spectral class proportion data of each land use type is analyzed.

Based on the results obtained from the three processes, we can start the classification work. As shown in Figure 3.7, after the training process, the spectral class composition data (e.g. x% class A, y% class B, z% class C) of each land use type (e.g. land use type I) are obtained. These data can assist in identifying land use types (e.g. in an area, if there is x% spectral class A, y% B, and z% C, we can conclude that this area belongs to land use type I).

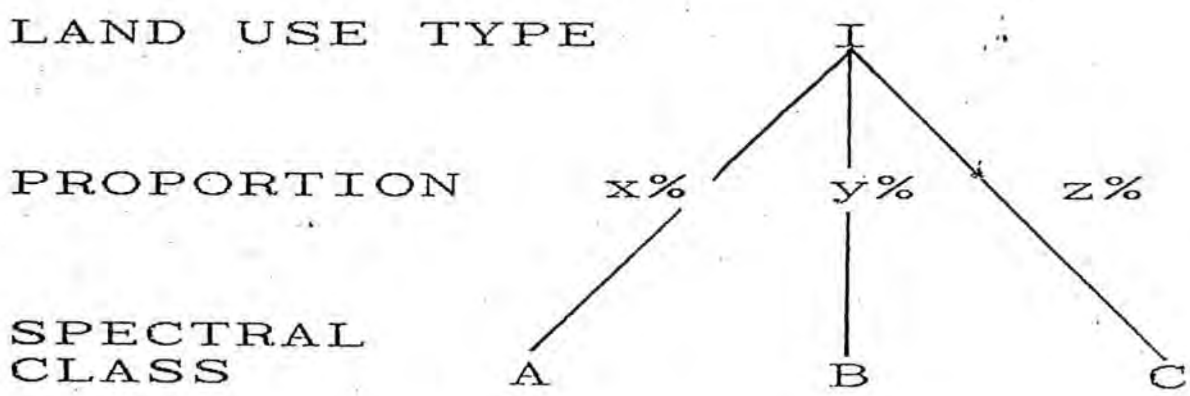


Figure 3.7 Relationship between a Land Use Type and the Spectral Classes Extracting from Training Process.

One point that should be noted is that using window algorithm in the proportion counting process may reveal a great spatial variation within the proportion data. As a result, it is difficult to apply the results from the training process directly in the classification of proportion data because the composition data extracted is too rigid and cannot accommodate spatial variation. However, the transect process is able to acquire the spatial variation of the proportion and provide a range of variation of the proportion (e.g. proportion for spatial class A may vary from x_1% to x_2%). The results from the training and transect processes should therefore be combined to compile the classification rules (Figure 3.8).

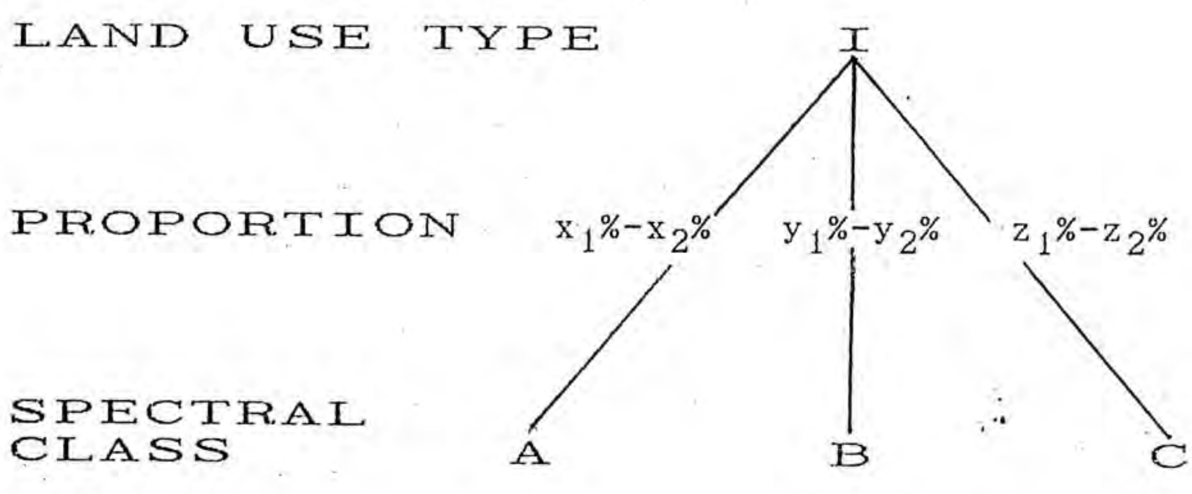


Figure 3.8 Relationship between a Land Use Type and the Spectral Classes Extracted from Training Process and Transect Process.

The rules are compiled as follows:

$$\text{If } (x_1\% \leqslant PA_i \leqslant x_2\%) \text{ and } (y_1\% \leqslant PB_i \leqslant y_2\%) \text{ and } (z_1\% \leqslant PC_i \leqslant z_2\%)$$

$$\text{then } LU_i \in \text{Land use type I}$$

PA_i : The proportion of the spectral class A at pixel i.
PB_i : The proportion of the spectral class B at pixel i.
PC_i : The proportion of the spectral class C at pixel i.
LU_i : The land use type at pixel i.

Different rules are set for different land use types and the whole image is classified according to these rules.

3.1.9 Summary

At this stage, the general outline of the new classification method has been illustrated. Its processes can be summarized as follows:

(a) Remote sensing data is classified into m spectral classes by using a simple per-pixel unsupervised classification.

(b) According to the land use classification scheme and with the help of suitable references (e.g. aerial photos, maps and etc.), the most appropriate training sites are chosen.

(c) To extract the spectral class composition data from the training sites. These data are used to find out the types of spectral classes constituted in each type of land use. The composition each spectral class constituted is extracted and used as classification rules.

(d) A n*n window will be set for each pixel to count the spectral class proportion. The proportion data of each spectral class is then stored in one channel and m channels of spectral class proportion data are resulted. These proportion data replace the data of spectral reflectance and is to be used as classification targets.

(e) To extract the spatial variation of the proportion through the transect process. These results can be used to amend the "rules" derived from the training process.

(f) Land use rules are used to classify the spectral class proportion data of the m channels by a rule-based classification method.

(g) Land Use Classification Maps are finally derived and subjected to accuracy assessment.

3.2 Research Design

3.2.1 Study Area

Hong Kong is situated at the estuary of the Pearl River in Southern Guangdong Province. Its location is at latitude 114°15' East and longitude 22°15' North. Its area is about $1000km^2$ which has accommodated 6 million population in 1991.

The study area which is about $100km^2$ and consists of is the main urban area in Hong Kong covers New Kowloon, Kowloon Peninsula, Victoria Harbor and the northern part of Hong Kong island (Figure 3.9). This area is chosen because of the existence of various types of land use with high internal heterogeneity in it.

. Figure 3.10 is the SPOT image (512*512 pixels) used in this study. It can be seen that the spatial variation of its spectral reflectance is great. In the figure, area A (Kowloon Tong) is a low density residential area, area B (Mei Foo) is a high density residential area while area C (Central) is a commercial area. We can observe that each type of land use has a great extent of spectral heterogeneity. To classify these areas, conventional per-pixel classifier may seem to be inadequate. These characteristics are considered more suitable for testing the new classification method.

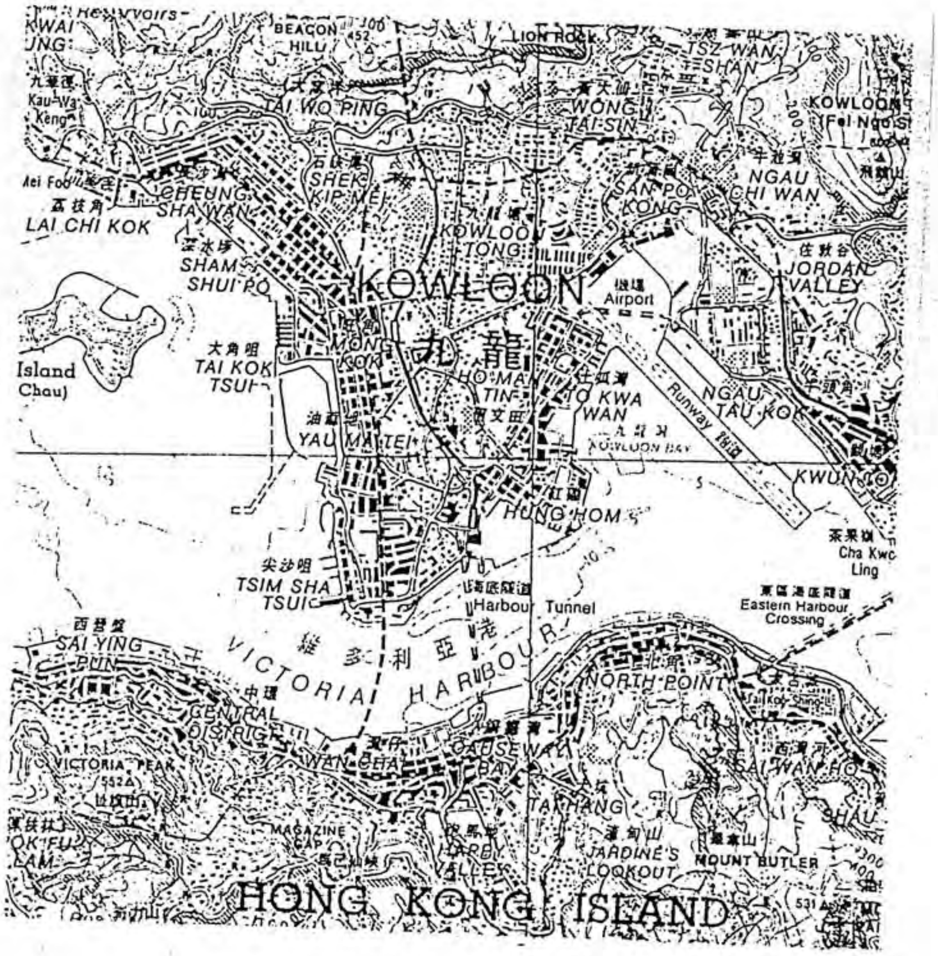


Figure 3.9 Study Area
(Survey and Mapping Office, 1991).

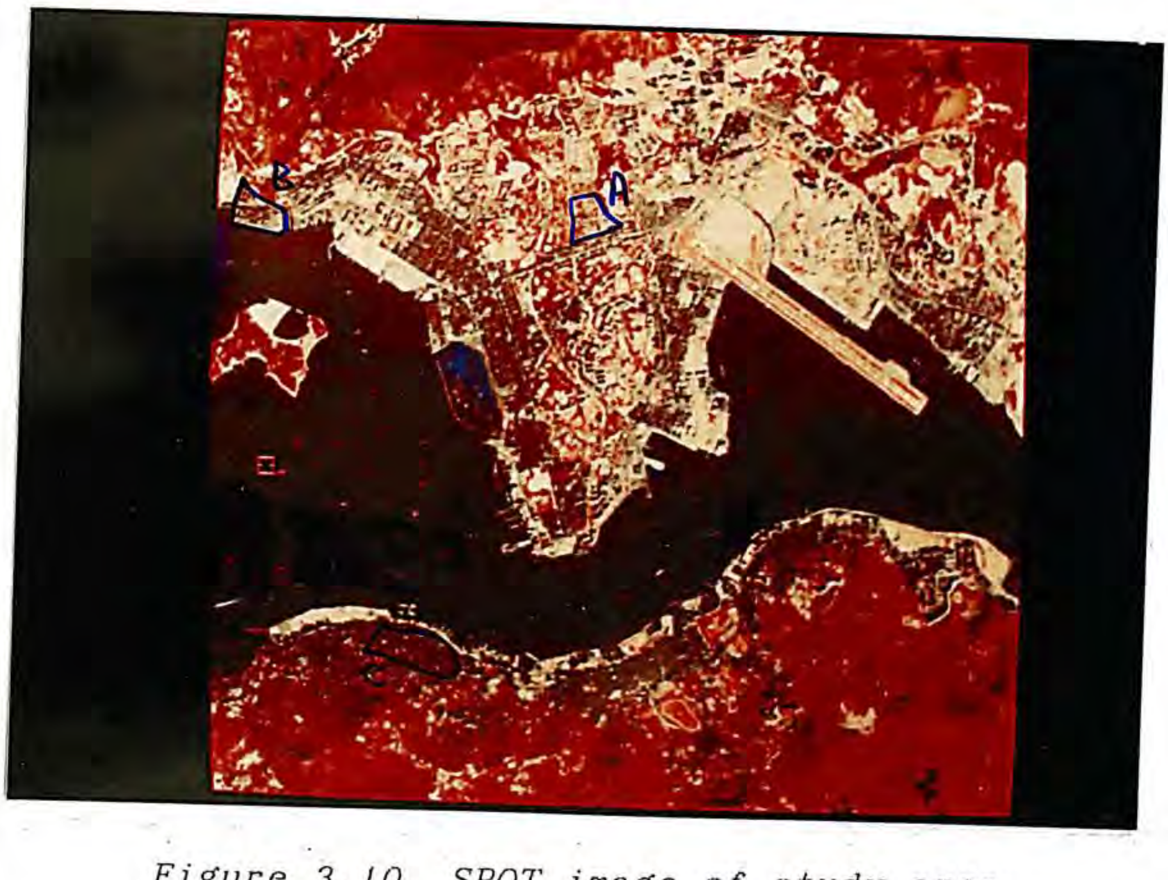


Figure 3.10 SPOT image of study area.

3.2.2 Data and Instruments Used

Data retrieved from an SPOT HRV (Multispectral mode) imagery dated 14 JAN, 1987 are used in this study. The spatial resolution of SPOT has already advanced to 20m*20m (Multispectral mode) and 10m*10m (Panchromatic mode) as compared with those of Landsat MSS (79m*79m) and TM (30m*30m). The more advanced the spatial resolution, the more suitable it is to be used to test the new method.

Image processing tasks are implemented on an 80386 micro computer with the EASI/PACE and IDRISI softwares. Programmes of SCCM are written in FORTRAN Language. Color (flying height 5,000", dated 7-11-86) and panchromatic (flying height 10,000", dated 21-12-86) aerial photos of the study area are used in the training process and for accuracy assessment.

3.2.3 Classification Scheme

Referring to the Government's Hong Kong Land Use Map (Town Planning Office, 1986), nine land use types are selected in the classification scheme. They are listed in Table 3.2.

Land uses (U_H.D.R., U_L.D.R., U_COM., U_IND., and U_PARK) and land covers (U_CWater, U_Twater, U_Veget., U_Opensp.) are used in association. This not only reflects the collection of data by satellite imagery (from which it is difficult to distinguish many activities) (Anderson, Hardy, Roach and Witmer, 1979) but also reflects the occasional inter-dependent nature of activity and form, and the conceptually fuzzy distinction between them (Rhind and Hudson, 1980).

Table 3.2 Land Use Classification Scheme

Class Name[1]	Land Use Types
1. U_H.D.R.	*High Density Residential Area*
2. U_L.D.R.	*Low Density Residential Area*
3. U_COM.	*Commercial Area*
4. U_IND.	*Industrial Area*
5. U_PARK	*Recreational Area*
6. U_OPENSP.	*Open Space*
7. U_VEGET.	*Vegetation*
8. U_CWATER	*Clear Water Bodies*
9. U_TWATER[2]	*Turbid Water Bodies*

3.2.4 Accuracy Assessment

In order to assess the effectiveness of the SCCM, accuracy assessment should be executed. Simple per-pixel

1. All land use types are printed in italic and are noted with a "U_" in front of the class names for distinction from spectral classes.

2. The meaning of 'turbid' in this study does not exactly equal to the term 'turbidity', which is caused by pollution, used in environmental science. 'Turbid' here represents water body that has greater spectral reflectance resulted not only from pollution but also from waves and other disturbance in the sea.

supervised classification (SPPC) is also applied in the classification and its results are to be assessed. The results from SPPC are mainly used for comparison with that of the SCCM. The steps of the assessment are as follows:

(1) A stratified systematic unaligned method is used in this study. A total of 400 sample points is extracted;

(2) With reference to aerial photos, the 400 sample points are classified under the classification scheme adopted in this study;

(3) These sample sites act as reference sample data with which the classified images are verified;

(4) Error matrix is produced after verification; and

(5) From the error matrix, the producer's accuracy, user's accuracy, overall accuracy and kappa coefficient are calculated. These indices are used as the standards for comparing the classification results, and the significance of the difference of kappa coefficient between the two methods (SCCM & SPPC) are tested.

The definitions of those indices are as follows:

(a) The producer's accuracy: the number of correctly classified samples of a particular land use type divided by the total number of reference samples for that land use type. It measures the error of omission.

(b) The user's accuracy: the number of correctly classified samples of a particular land use type divided by the total number of samples being classified as that land use type. It is a measure of commission error.

(c) The overall accuracy: the total number of correctly classified samples (diagonal cells of the matrix) divided by the total number of samples. It measures the accuracy of the entire image without any indication of the accuracy of individual categories.

(d) The Kappa coefficient of agreement (kappa) was developed by Cohen (1960). It is a measure of the actual agreement —— "Observed" (indicated by the diagonal elements of the matrix) minus chance agreement —— "Expected" (indicated by the product of row and column marginal). It uses all cells in the matrix and takes into account both the commission and omission errors (Rosenfield and Fitzpatrick Lins, 1986). The general form of kappa is defined as follows:

$$\text{kappa} = \frac{\text{Observed} - \text{Expected}}{1 - \text{Expected}}$$

CHAPTER 4

RESULTS AND DISCUSSION I — EXAMINING THE RELATIONSHIP BETWEEN LAND USE AND SPECTRAL CLASSES

The results of the method are illustrated in this chapter. First, three different spectral class maps are derived from the unsupervised classification process. Second, Spectral class composition results of each land use type are obtained from the training process. These results help us understand the internal structure of the land use types and the hypothesis that one land use type consists of more than one spectral class is tested. Third, Proportion Counting is carried out. The spectral class proportion data within n*n pixels surrounding each pixel is counted. The spatial variation of the proportion is analyzed through the transect process, from which, classification rules for each land use type are derived.

4.1 Unsupervised Classification

4.1.1 Unsupervised Classification Process

The unsupervised classification method used in this study is based on the EASI/PACE image processing system. This process can be generally divided into two steps. First, Histogram Clustering Method is used to find out the representative cluster means of spectral data within an image. Second, these cluster means are used in a Maximum Likelihood classification to find out the most similar cluster mean for each pixel. Each pixel can then be classified as belonging to one of the clusters. Each cluster composed of a group of pixels of similar spectral characteristics forms a spectral class. Finally, the cluster labeling process finds out the corresponding information class for each spectral class.

Unfortunately, in the unsupervised classification process of the EASI/PACE system, the maximum number of spectral classes that can be derived is only sixteen. Sixteen types of spectral classes are inadequate for a complex classification scheme. It poses limitation on testing the Spectral Class Composition Method (SCCM).

4.1.2 Unsupervised Classification Results

Limited by the number of sixteen classes, this study examines the effects of using different number of spectral classes on the SCCM. The three numbers of classes are 3 classes, 9 classes and 15 classes. The unsupervised classification method is implemented three times, each time using different numbers of classes. Three maps composed of 3, 9, and 15 spectral classes maps are derived. The classification results of the maps are illustrated in Tables 4.1, 4.2 and 4.3.

Table 4.1 Results of the 3-class Unsupervised Classification.

Class No.	No. of Pixels	Percentage of the whole map
1.	79999	30.5
2.	110285	42.1
3.	66244	25.3
Unclassified	5616	2.2

Table 4.2 Results of the 9-class Unsupervised Classification.

Class No.	No. of Pixels	Percentage of the whole map
1.	123	0.0
2.	20249	7.7
3.	2665	1.0
4.	45254	17.3
5.	51106	19.5
6.	34806	13.3
7.	39432	15.0
8.	47925	18.3
9.	15779	6.0
Unclassified	4805	1.8

Table 4.3 Results of the 15-class Unsupervised Classification.

Class No.	No. of Pixels	Percentage of the whole map
1.	0	0
2.	160	0.1
3.	1825	0.7
4.	19079	7.3
5.	205	0.1
6.	16832	6.4
7.	50402	19.2
8.	27537	10.5
9.	112	0.0
10.	0	0
11.	761	0.3
12.	30839	11.8
13.	48900	18.7
14.	33238	12.7
15.	24547	9.4
Unclassified	7707	2.9

The advantages and disadvantages of the unsupervised classification method have already been discussed in Chapter 3. There is one major defect in this method, i.e. it is difficult to match the spectral classes derived with the information classes required by the analysts. They may only represent some mixed types of ground feature or the numbers of pixels of these classes are too small.

Analyzing the classification results at Tables 4.1, 4.2, and 4.3, it is found that the numbers of pixels of a number of classes are less than 1% of the whole image. These classes are usually those that are difficult to be matched with the informational classes. In the 9-class image (Table 4.2), the number of pixels of the first and the third classes are 123 and 2665 respectively. They constitute 0.04% and 1.02% of the entire image respectively. In the 15-class image (Table 4.3), the first, second, third, fifth, ninth, tenth, and eleventh classes have 0, 160, 1825, 205, 112, 0, and 761 number of pixels respectively, constituting only 0%, 0.1%, 0.7%, 0.1%, 0.04%, 0%, and 0.3% of the entire image. For other spectral classes, it is easier to identify the land cover they represent and their characteristics.

The result of the 3-class image are the simplest. They are listed at Table 4.4 while Figure 4.1 shows the map of the 3 class unsupervised classification.

Table 4.4 Spectral Classes of the 3-Class Map.

No.	Name	Ground Features	Color
1.	WATER	Water bodies & Shadow of high density buildings	Blue
2.	VEGET	Vegetation & High density buildings	Green
3.	BARESOIL	Baresoil & Low density buildings	White

Figure 4.1 The 3-Class Unsupervised Classification Result Map.

Similarly, Table 4.5 lists out the classes of the 9-class map and Figure 4.2 illustrates the unsupervised classification results.

Table 4.5 Spectral Classes of the 9-Class Map.

No.	Name	Ground Features	Color
1.	UNCLASSIFIED	Vegetation?	Black
2.	VEGET1	Vegetation on shadowed slope	Mossy Green
3.	UNCLASSIFIED	Vegetation?	Black
4.	CWATER	Clear Water Bodies	Blue
5.	VEGET2	Vegetation on illuminated slope	Green
6.	TWATER	Turbid water bodies & Shadow of high density buildings	Purple
7.	H.D.Build.	High density buildings	Red
8.	L.D.Build.	Low density buildings	Orange
9.	Baresoil	Bare Soil	White

?: the no. of pixels is too small for identification of its nature.

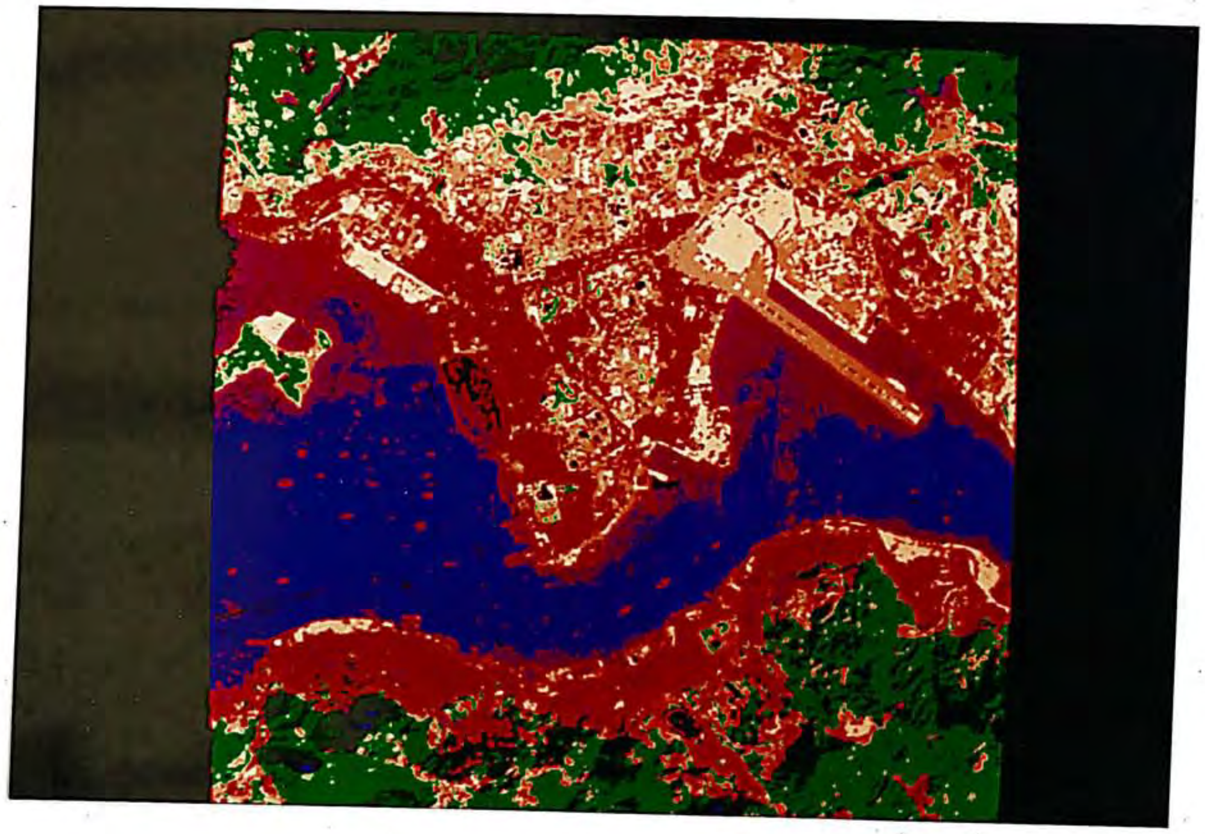


Figure 4.2 9-Class Unsupervised Classification Result Map.

The spectral classes of the 15-class map are listed in Table 4.6 while unsupervised classification of the map is shown in Figure 4.3.

Table 4.6 Spectral Classes of the 15-Class Map.

No.	Name	Ground Features	Color
1.	UNCLASSIFIED	NIL	Black
2.	UNCLASSIFIED	Vegetation?	Black
3.	UNCLASSIFIED	Vegetation?	Black
4.	VEGET1	Vegetation on shadowed slope	Mossy Green
5.	UNCLASSIFIED	NIL	Black
6.	CWATER	Clear Water Bodies	Blue
7.	VEGET2	Vegetation on illuminated slope	Green
8.	TWATER1	Turbid water bodies	Purple
9.	UNCLASSIFIED	Vegetation?	Black
10.	UNCLASSIFIED	NIL	Black
11.	UNCLASSIFIED	Shadow?	Black
12.	TWATER2	Very turbid water bodies & Shadow of high density buildings	Light Blue
13.	L.D.Build.	Low density buildings	Orange
14.	H.D.Build.	High density buildings	Red
15.	Baresoil	Bare Soil	White

?: the no. of pixels is too small for identification of its nature.

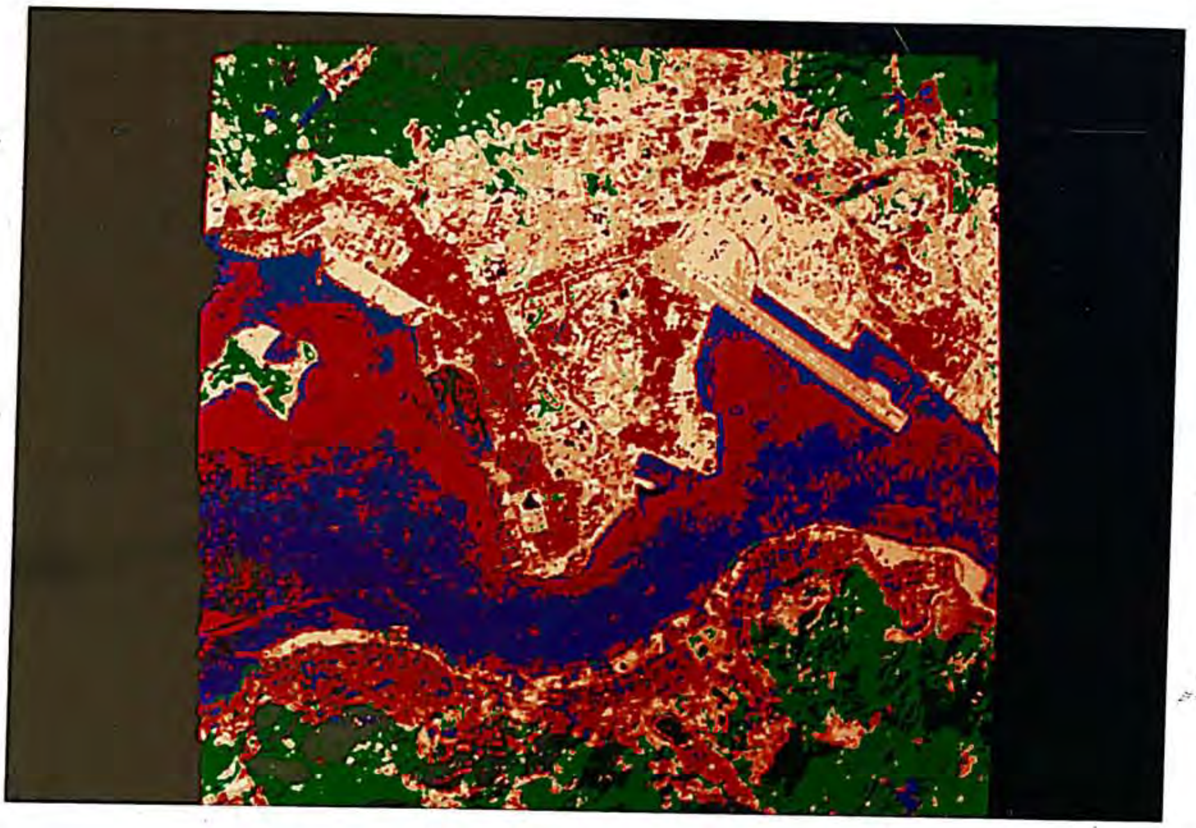


Figure 4.3 15-class unsupervised classification result map.

4.1.3 Difference Between Spectral Class Maps

Observing the distribution of spectral classes among the three unsupervised classification maps, the differences among them can be traced. Table 4.7 illustrates the relationships of the various classes among the 3 maps. The 3-class map is the simplest one while the 9-class and 15-class maps show greater details. For instance, the class of Water Bodies/ Shadow in the 3-class map is further divided into Clear Water and Turbid Water/ Shadow in the 9-class one. In the 15-class map, the class of Turbid Water is further subdivided into Turbid Water and Very Turbid Water/ Shadow.

Table 4.7 Relationships Between the Various Classes among the Three Unsupervised Classification Maps.

3-class map	9-class map	15-class map
1. WATER	4. CWATER 6. TWATER	6. CWATER 8. TWATER1 12. TWATER2
2. VEGET	2. VEGET1 5. VEGET2 7. H.D.BUILD	4. VEGET1 7. VEGET2 14. H.D.BUILD.
3. BARESOIL	8. L.D.BUILD. 9. BARESOIL	13. L.D.BUILD. 15. BARESOIL

The class of Vegetation/ High Density Buildings in the 3-class map is divided into three classes namely Vegetation on Shadowed Slope, Vegetation on Illuminated Slope, and High Density Buildings in the 9-class and 15-class maps. The class of Bare Soil/ Low Density Buildings in 3-class map is divided into Low Density Buildings and Bare Soil in the 9-class and 15-class ones.

In the 3-class map, ground features (spectral classes) have been generalized and classified into three classes only. This generalization surely hinders further analysis and leads to ambiguities in understanding the ground features. In the SCCM, the identification of land use classes depends on observing the different compositions of these spectral classes. Over-generalization of these classes affects the accuracy of the results. On the contrary, with an increased number of spectral classes, the spatial distribution of ground features can be more clearly shown. It also enables us to identify the different land use classes through observing the compositions of the spectral classes. The major difference between the 9-class and 15-class map is that the class of Turbid Water/ Shadow in the 9-class map is further divided into two classes in the 15-class map. They are Turbid Water and Very Turbid Water/ Shadow. The other classes are less important as the number of pixels attached are too small which makes them difficult to be regarded as individual classes.

4.2 Training Process

4.2.1 Definition of Training Process

Training process is the first step taken in the supervised classification method. In this process, representative training sites are selected for each target information class in the image. This selection depends mainly on human interpretation of spectral data of the image and is complemented by the use of ancillary information (including maps, aerial photos and field study results etc.). Statistics of the spectral data of these sites are extracted for classifying the entire image.

In the conventional methods, it is assumed that spectral data of the training areas are homogeneous. In other words, it is assumed that the spectral characteristics of one informational class are homogeneous. When selecting training areas, much emphasis is thus placed on whether the data of the areas are homogeneous.

The hypothesis of this study however assumes that land use types are often formed by more than one spectral class. The anticipated results of the training process is therefore different. Spectral data of the training areas are not homogeneous but, on the contrary, are to a great extent heterogeneous. In order to find out the degree of heterogeneity, the statistics that are going to be extracted are not the spectral data of the image. It focuses on examining the relationships between land use types and the spectral classes resulted from the unsupervised classification. After this examination, whether one land use type is formed by more than one spectral class can be verified. If the answer is confirmed, it can then proceed to find out the types of spectral classes that form each land use type.

4.2.2 Selection of Training Areas

As mentioned in the above, this study does not consider the homogeneity of the spectral data in the selection of training areas. The selection is based on the reference of aerial photos or field study results. Three to five training sites are selected for each land use in the training process. Their respective locations are listed in Table 4.8.

Table 4.8 Training Sites of Land Use Types.

Land Use Class	Training Sites
1. U_H.D.R.	Mei Foo, Tai Koo, Sham Shui Po & Choi Hung Est.
2. U_L.D.R.	Kowloon Tong, Yau Yat Chuen, Jardine's Lookout & The Peak
3. U_COM.	Central District, Admiralty & Wan Chai
4. U_IND.	Cheung Sha Wan, San Po Kong & Kwun Tong
5. U_OPENSP.	Reclaimed land at Sham Shui PO, Hung Hom, Sai Ying Pun and Quarry Bay
6. U_PARK	Morse Park, Kowloon Tsai Park, Kowloon Park & Victoria Park
7. U_VEGET	Kowloon Peak, Tate's Cairn, Golden Hill & Mt. Butler
8. U_WATER	Three sites in Victoria Harbour
9. U_TWATER	Three sites in Victoria Harbour

*please refer to Table 3.2 for the name of land use types.

In fact, the training sites selected are typical representations of the land use in Hong Kong. The spectral class composition of each land use type can therefore be observed.

4.2.3 Spectral Class Composition Data Extracting From the Training Sites

When examining the relationship between land use and spectral classes, training data extraction is implemented three times since there are three different numbers of spectral classes (3, 9, 15 classes). The proportion of spectral classes in each land use type is counted.

Table 4.9 shows the proportion data extracted from the 3-class map. It is observed that one land use type often consists of more than one spectral class. For example, in the land use type of *high density residential area*, there are 18.7% shadow of building, 61.5% high density buildings as well as 19.8% low density buildings and bare soil. In the real situation, there are roads, recreational facilities and commercial complexes in the *high density residential area*. This shows that such land use type is not only composed of high density buildings but also made up of some bare soil and low density buildings. On the other hand, the high land value in *commercial area* only allows the occurrence of fewer recreational facilities. Therefore, the *commercial area* is largely composed of high rise buildings and their shadow in the training results.

Table 4.9 Spectral Composition Data Extracted from the 3-Class Map.

	SPECTRAL CLASSES			
LAND USE	WATER	VEGE	BS	TOTAL
1 U_H.D.R.	18.69	61.50	19.80	100
2 U_L.D.R.	0.59	44.55	54.86	100
3 U_COM	48.01	45.74	6.24	100
4 U_IND	10.09	54.04	35.86	100
5 U_PARK	0.05	38.32	61.62	100
6 U_OPENSP	0.18	0.66	99.15	100
7 U_VEGET	1.41	97.61	0.98	100
8 U_CWATER	100	0	0	100
9 U_TWATER	100	0	0	100
TOTAL	279.0	342.4	278.5	900

From the results, it is also found that some land use types are relatively homogeneous. For example, *open space* consists of 99% bare soil. *Vegetation* is another typical example which mainly correspond to one dominating spectral class, i.e. vegetation (97.6%). *Clear and turbid water bodies* comprise even 100% of the spectral class of water.

The composition data extracted from 9-class map are listed in Table 4.10. As the number of classes increases, the classification gives greater details. This enables a clearer observation of the composition of spectral classes. With the addition of new spectral classes, the homogeneous land use types in the 3-class map thus become heterogeneous. For instance, *open space* consists of 86.9% bare soil and 12.1% low density buildings. *Vegetation* is composed of 25% vegetation on shadowed slope and 65.2% vegetation on illuminated slope.

Table 4.10 Spectral Composition Data Extracted from the 9-Class Map.

	SPECTRAL CLASSES								
		VEGET1		WATER	V2	TWATER	H.D.	L.D.	BS
LAND USE	1	2	3	4	5	6	7	8	9
1 U_H.D.R.	0	0.028	0	0	0.03	20.82	69.90	8.61	0.6
2 U_L.D.R.	0	2.49	0.15	0	13.49	0.81	21.74	55.07	6.23
3 U_COM	0	0	0	0	0	49.24	48.67	2.08	0
4 U_IND	0	0.20	0	0	0.16	12.85	65.38	19.40	2
5 U_PARK	0	0.51	0	0	21.28	0.06	7.29	58.39	12.46
6 U_OPENSP	0	0	0	0	0.07	0.14	0.79	12.14	86.85
7 U_VEGET	0.47	25.02	3.27	0	65.19	1.95	1.67	2.42	0.01
8 U_CWATER	0	0	0	99.8	0	0.20	0	0	0
9 U_TWATER	0	0	0	9.33	0	90.67	0	0	0
TOTAL	0.466	28.25	3.414	109.1	100.2	176.7	215.4	158.1	108.1

Table 4.11 shows the proportion data extracted from the 15-class map. The results are similar to that of the 9-class one. The only major difference is that turbid water is further divided into turbid water and very turbid water in 15-class map. This has increased the degree of heterogeneity of the internal structure of the two land use types of *water bodies*. *Clear Water Bodies* is composed of 75.6% clear water , 14% turbid water and 10.3% very turbid water while *turbid water bodies* has 58.4% turbid water and 41% very turbid water.

Table 4.11 Spectral Composition Data Extracted from the 15-Class Map.

SPECTRAL CLASSES

LAND USE	1	2	3	VEGET1 4	5	CWATER 6	VEGE 7	TWATER1 8	9	10	11	TW2 12	L.D. 13	H.D. 14	BS 15
1 U_H.D.R.	0	0	0	0	0	0	0	0	0	0	0.06	17.42	14.13	66.99	1.39
2 U_L.D.R.	0	0	0.18	1.54	0	0	11.31	0	0.04	0	0	0.59	60.40	13.77	12.16
3 U_COM	0	0	0	0	0	0	0	0	0	0	1.51	43.85	3.78	50.85	0
4 U_IND	0	0	0	0.04	0	0	0.12	0	0	0	0	10.23	28.22	56.87	4.51
5 U_PARK	0	0	0	0.23	0	0	19.47	0	0	0	0	0.06	49.09	4.76	26.38
6 U_OPENSP	0	0	0	0	0	0	0.07	0	0	0	0	0.11	5.57	0.60	93.64
7 U_VEGET	0	0.52	1.81	24.97	0	0	65.26	0	0.02	0	0.01	1.52	2.65	3.21	0.03
8 U_CWATER	0	0	0	0	0	75.63	0	14.07	0	0	0	10.29	0	0	0
9 U_TWATER	0	0	0	0	0	0	0	58.37	0	0	0	41.62	0	0	0
TOTAL	0	0.52	2	26.77	0	75.63	96.25	72.45	0.06	0	1.58	125.6	163.8	197.0	138.1

4.2.4 Spectral Heterogeneous Characteristics of Land Use Types

Figures 4.4, 4.5, and 4.6 are bar charts illustrating the composition of various land use types. It is found that most of the land use types, especially the five types of *urban land use* (i.e. *high density residential area, low density residential area, commercial area, industrial area and recreational area*), are spectrally heterogeneous. The results of different training processes also show that these land use types are always composed of two or more spectral classes. Moreover, no one type of spectral class constitutes more than 70% of each land use. The more the number of classes, the more obvious this phenomenon is.

The other four land use types of *open space,*

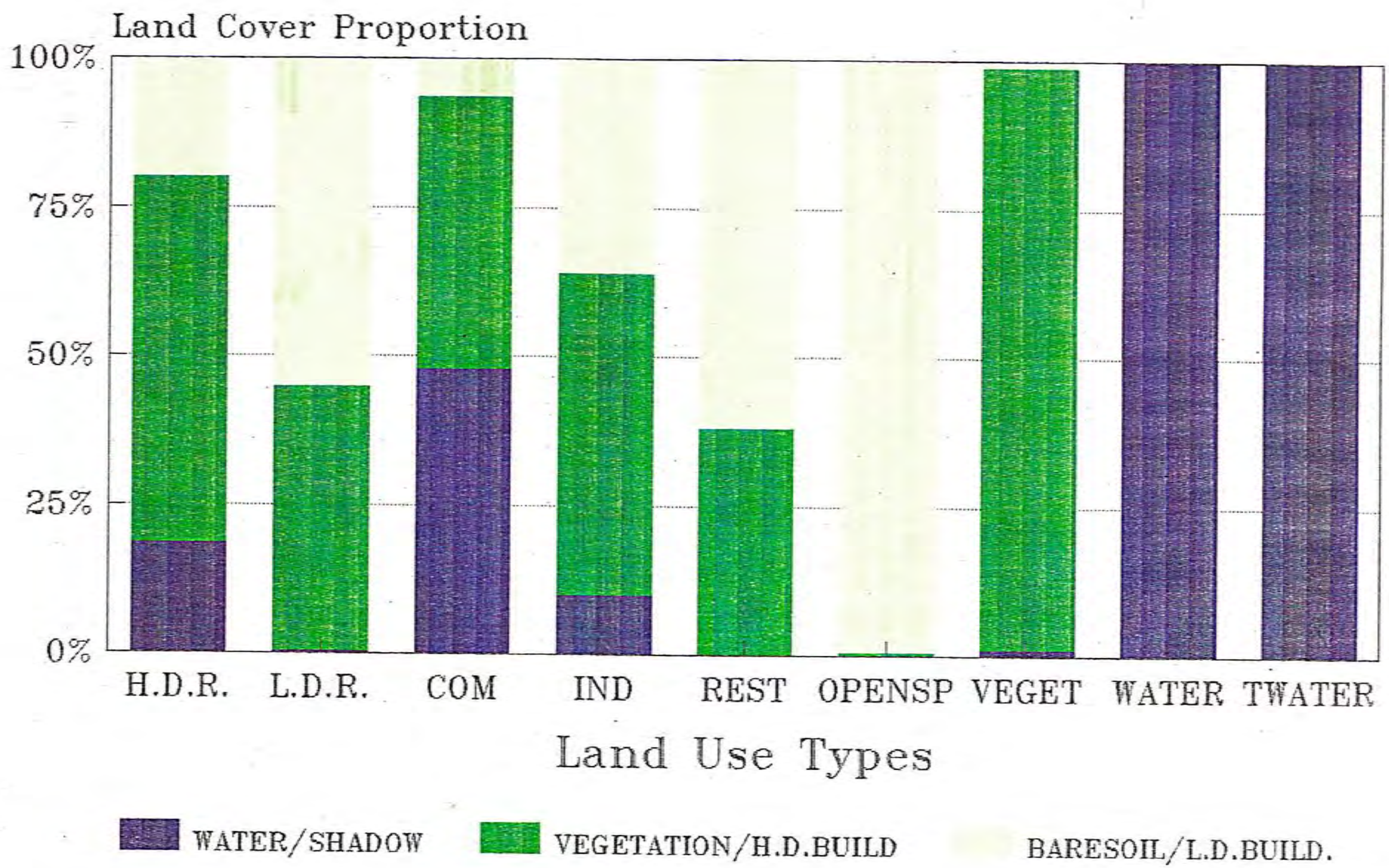


Figure 4.4 The Relationship Between Land Use Type & 3 Spectral Classes

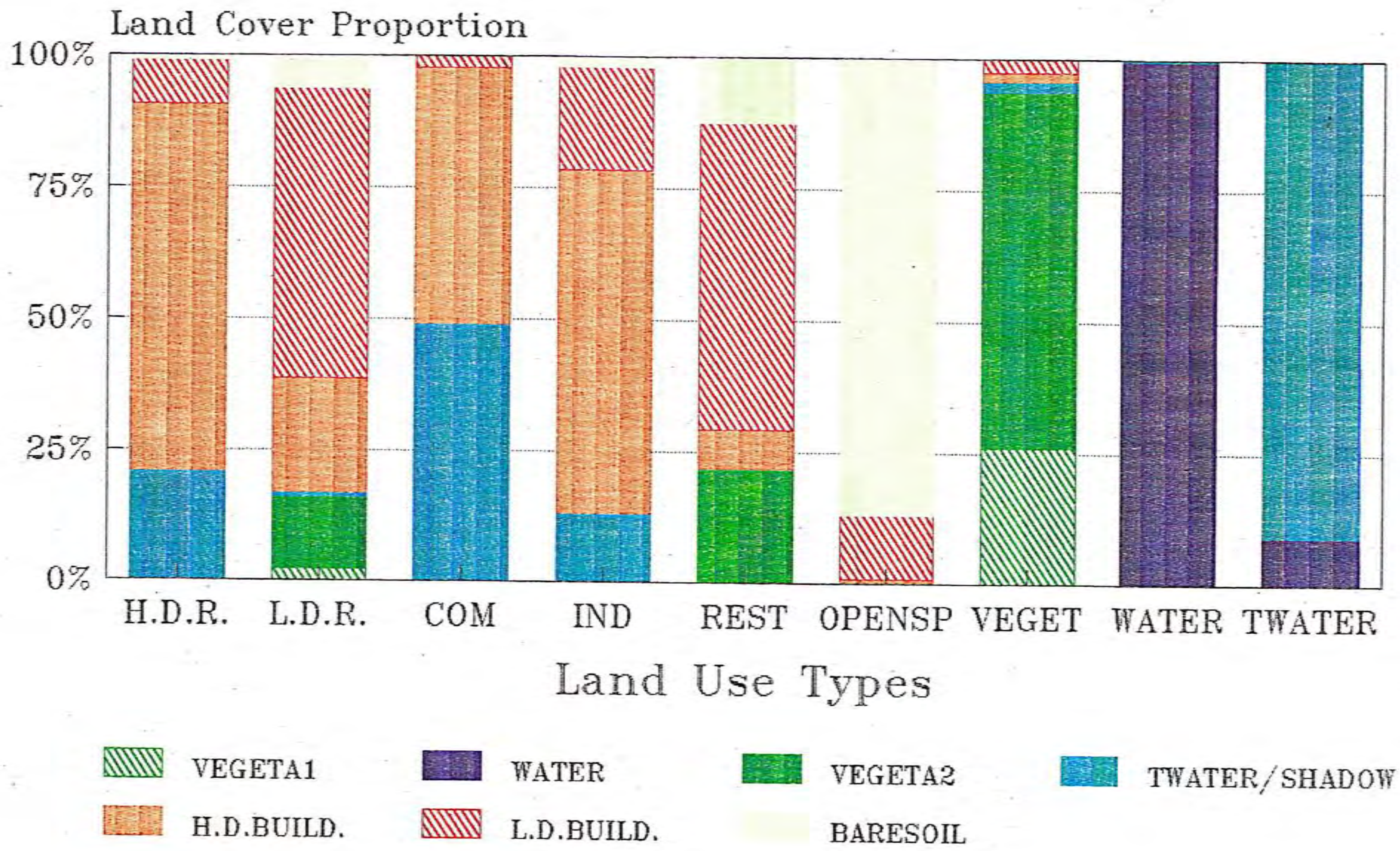


Figure 4.5 The Relationship Between
Land Use type & 9 Spectral Classes

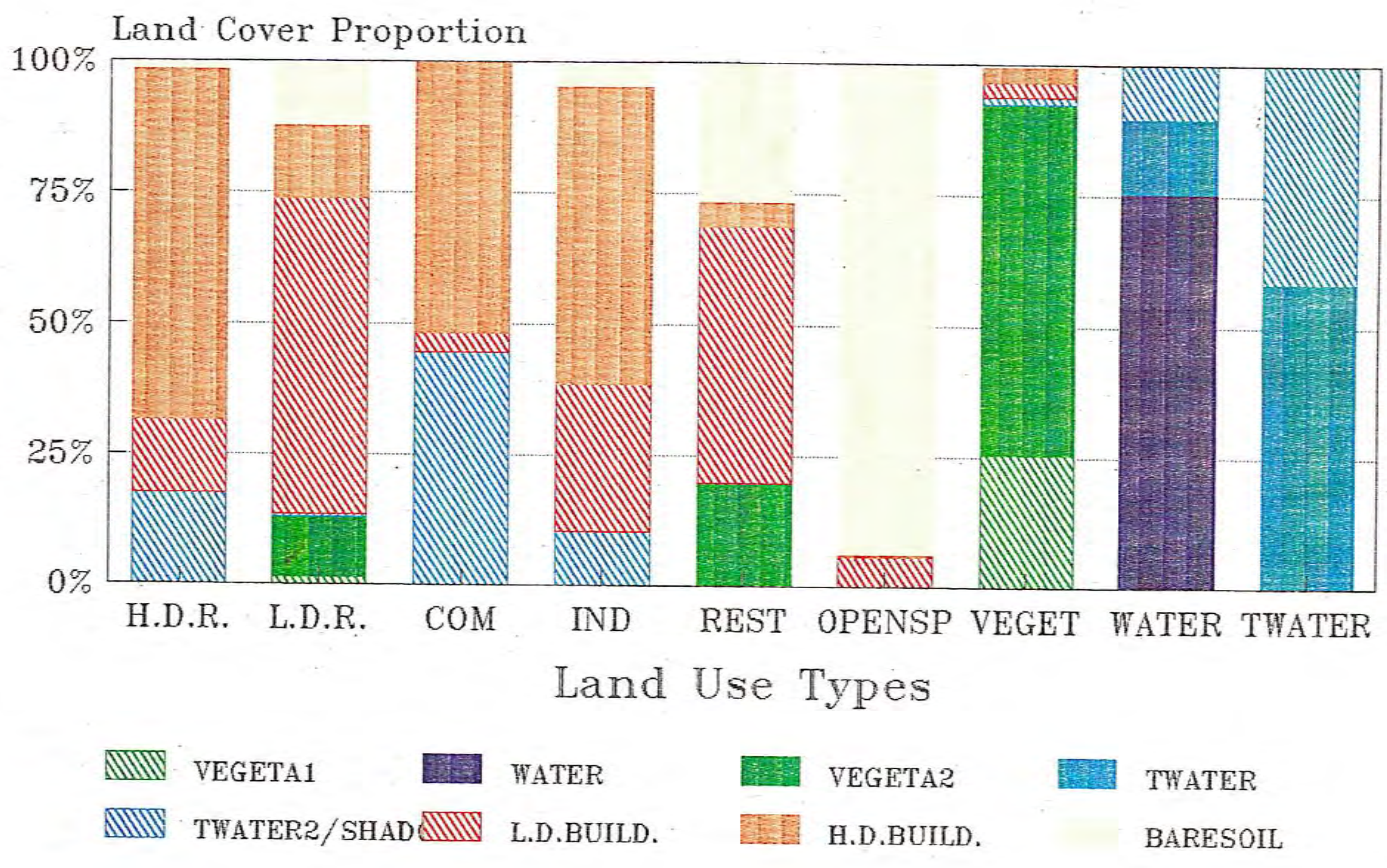


Figure 4.6 The Relationship Between
Land Use type & 15 Spectral Classes

vegetation, clear water bodies and turbid water bodies also have heterogeneous characteristics. However, as the number of classes decreases (eg. in 3-class map), the internal structure of these land use types become homogeneous and are largely composed of only one spectral class. With more spectral classes, the internal structure can be described in greater details and the land use types can then correspond to more than one spectral class. The internal structure of *open space*, however, still mainly corresponds to only one spectral class of bare soil.

4.2.5 Different Number of Spectral Classes

The spectral class composition of each land use is different if different numbers of spectral classes are used. When the number of classes is small, such as in the case of 3 classes, the ground features with similar spectral reflectance are grouped into one type. This may affect the identification of land use types by observing spectral class composition. As shown in Figure 4.4, it is found that the spectral class compositions of the two land use types of *clear and turbid water bodies* are the same. It is because the clear and turbid water bodies on the land surface are grouped into one spectral class in the unsupervised classification. It becomes impossible to make use of it to identify the spectral class composition of the land use types.

Other land use types have a similar situation. Take *open space* as an example, when using the 3-class map for analysis, baresoil and low density buildings are grouped into one spectral class in unsupervised classification. Difficulties are thus encountered in studying the proper structure of *open space*. In addition, it is also difficult to differentiate *low density residential area* from *recreational area* due to over-generalization of their spectral class composition.

On the contrary, the training data extracted from the 9-class map show greater details and give a clearer composition result (Figure 4.5). For example, the spectral classes of clean and turbid water can be used to identify the land use types of *clean water and turbid water bodies*. The structure of the land use types of *open space and vegetation* are no longer homogeneous. They have included other types of spectral classes. Similarly, the structures of *low density residential area and recreational area* are described in greater details, they thus can be differentiated from each other more distinctly.

Regarding the 15-class map (Figure 4.6), it is originally anticipated that it can illustrate each land use type more clearly. However, as mentioned in section 4.1, some classes of the map have only few pixels attached. The contribution of them in understanding the structure of land use types is thus limited. As a result, the spectral composition results of 9-class and 15-class maps become similar. The only major difference is that turbid water is further divided into turbid water and very turbid water in the 15-class map, which enables a more detailed identification of *water bodies*. From the above, it can be inferred that with an increased number of spectral classes, the land use structures can be understood more clearly. Unfortunately, this is often limited by the capacity of the software.

On the other hand, as mentioned earlier in section 4.1.2, in the 15 spectral classes map, some spectral classes are not included or only a small proportion of them are included into the structure of land use types in the training areas. These classes have too few pixels attached and are difficult to be regarded as individual classes. A similar situation also occurs in the 9-class map. As illustrated in Table 4.10, the spectral class composition that the 1st and 3rd classes constituted in the 9 land use types (total 900%) are 0.5% and 3.4% respectively. Their effects are minimal. For the 15-class map (Table 4.11), the 1st, 2nd, 3rd, 5th, 9th, 10th and 11th classes have proportion that amount to 2% only in the total of 900% (9 land use types). Their effects are thus minimal too. Thus, they are not used in the following classification steps.

4.2.6 Similar Composition Results in Some Land Use Types

From the training results (Figures 4.4, 4.5 and 4.6), it is found that some land use types consist of similar compositions. For instance, *high density residential area, commercial and industrial area* are mainly composed of high density buildings and their shadow. *Low density residential area and recreational area*, on the other hand, are composed of low density buildings ,vegetation, some bare soil and high density buildings. These particular cases are derived from the special characteristics in the study area of Hong Kong.

Hong Kong is characterized by little flat land but dense population. High rise buildings are established everywhere. No matter in the *high class or low class residential areas, industrial or commercial areas*, high rise and dense buildings are the main features. As a result, the spectral reflectance and thus the spectral class composition of these area are similar. The same reason also contributes to the similar composition of the *low density residential area and recreational area*. The *recreational area* in Hong Kong, different from the vast recreational area in other countries, is small and usually scattered among the buildings as parks. The spectral class composition of *recreational area* thus becomes similar to that of *low density residential area*. Such situation may have adverse effects on the classification results.

4.2.7 Using Spectral Class Composition Data as Classification Rules

From the results of the training process, it is found that each land use type is usually composed of more than one type of spectral classes. Though the structures of some land uses are mainly homogeneous, there are still the occurrence of several spectral classes other than the major ones. This can prove that the first hypothesis of this study is valid. On the other hand, on spectral class can be included into more than one land use type while such cannot be shown by simple per-pixel classifier. The next step is the establishment of a more appropriate classification method with the aim of increasing the classification accuracy.

Through the training process, the spectral class composition of each land use type has been found. The composition data can clearly describe the internal structure of the land use types. For example (Table 4.9), by knowing that there are 18.7% shadow, 61.5% high density building and 19.8% baresoil/ low density building within a definite area, it can be decided that the land use within this definite area is most likely *high density residential area*. This composition data can then be established as a "rule" for further classification.

However, the following should be considered before classification: (a) How to convert all remote sensing data to spectral class composition data? and (b) How to define the upper and lower limits of the composition rules?

4.3 PROPORTION COUNTING

4.3.1 Window-Based Proportion Counting Process

In the training process, with reference to ancillary information and knowledge of the study area, training sites with clear-cut boundary are selected. The extraction of spectral class composition data within the boundary also becomes possible. Nevertheless, in actual classification, it is impossible to know all the boundaries of land use blocks in advance. Methods should thus be devised to convert the per-pixel data into spatial composition data.

Under such circumstances, a window algorithm is considered to be the most appropriate method. Window algorithm has been applied in textural analysis, in which a surrounding n*n area for each pixel is drawn as a window. Textural data e.g. mean, median, standard deviation etc. are extracted within the window. The extracted results are then recorded in the central pixel and form new images for analysis.

In this study, a similar method is applied. First, window based composition data extraction is applied to the unsupervised classification map. That means, a window of n*n pixels is established for each pixel. According to the unsupervised classification results, the proportion that each spectral class constitutes within the window is then counted. The resulted proportion is recorded in the central pixel. The composition of each spectral class forms a channel. As the result, the spectral class composition data within a definite area (i.e. the n*n pixel) is extracted. The data is further processed by a rule-based classifier under which the rules derived from the training process are used to determine the land use class that each pixel belongs to. In order to distinguish the results derived from the training process and the proportion counting, the results of the former one is called composition data while the latter one is called proportion data.

The size of the window has determinant effect on the proportion data. The 5*5, 9*9 and 15*15 pixels, representing 100m*100m, 180m*180m and 300m*300m on the actual earth surface respectively, are used for proportion counting. As there are three unsupervised classification maps, the number of proportion counting that should be undertaken is nine. They are listed in Table 4.12.

Table 4.12 Nine types of Proportion Counting Processes.

Name	Proportion Counting Type	No. of Channels
1. 3c5w	3-class 5*5 Window Proportion Counting	3
2. 3c9w	3-class 9*9 Window Proportion Counting	3
3. 3c15w	3-class 15*15 Window Proportion Counting	3
4. 9c5w	9-class 5*5 Window Proportion Counting	7
5. 9c9w	9-class 9*9 Window Proportion Counting	7
6. 9c15w	9-class 15*15 Window Proportion Counting	7
7. 15c5w	15-class 5*5 Window Proportion Counting	8
8. 15c9w	15-class 9*9 Window Proportion Counting	8
9. 15c15w	15-class 15*15 Window Proportion Counting	8

As mentioned in section 4.2, some classes in the 9-class and 15-class maps have only few pixels attached. Since these classes do not help in understanding the spectral class composition of the land use types, they are not included in the proportion counting process. As a result, only the proportion of seven classes in the 9-class map is counted and recorded in 7 channels in the process. In the 15-class map, only the proportion of eight classes is counted and recorded in eight channels. According to the 9 types of proportion counting, the work of classification is implemented for nine times. Totally, fifty-four channels of spectral class proportion data are resulted.

4.3.2 Transect Process

The spectral class composition characteristics of different land use types are available. The spectral class proportion within the n*n window of each pixel has also been counted. Theoretically, the composition characteristics of the land use types can be used as "rules" to classify the image. However, the characteristics of the rules extracted from the training sites and the spectral class proportion counted from the window may not be totally correlated because of the different methods used. Another training process is therefore required to analyze the spectral class proportion characteristics and variations.

Transects are used to analyze the variation of the spectral class composition within the training areas. The location of the training sites for the various land use types in Table 4.8 is used again. The proportion data are counted along the transect from the fifty-four channels derived from proportion counting. The data extracted reveal the spatial variation of the proportion data.

Figure 4.7 (page 90) shows a transect drawn in the *low density residential area* (Kowloon Tong). Proportion data are extracted along this transect, based on the proportion counting results of the 5*5 window of the 15-class map. The X axis represents the location of the transect, i.e. pixel 228 to pixel 241. The Y axis represents the proportion counted in each spectral class. Spatial variation of the spectral class proportion data derived from the window based proportion counting is analyzed.

Table 4.13-4.21 illustrates the spectral class proportion data of the nine types of land use. The data show the upper and lower limits of their variation along the transect. Referring to Table 4.13, the lower limit of spectral class — WATER — in land use type — U_HDR — is 4, and the upper limit is 48. It means that the land use of *high density residential area* should consist of about 4% to 48% of water (shadow of high rise buildings). Following the same principle, The *high density residential area* also consists of about 36% to 84% high density buildings (VEGE) and 4% to 56% bare soil and low density buildings (BS).

Table 4.13 Transect Results of 3C5W Proportion Counting.

	SPECTRAL CLASSES					
	WATER		VEGE		BS	
LAND USE	LOW	UP	LOW	UP	LOW	UP
U_HDR	4	48	36	84	4	56
U_LDR	0	0	0	28	72	96
U_COM	12	68	20	56	4	36
U_IND	20	36	44	80	0	36
U_PARK	0	8	32	92	8	68
U_OPENSP	0	16	0	8	68	100
U_VEGETA	0	0	100	100	0	0
U_CWATER	100	100	0	0	0	0
U_TWATER	100	100	0	0	0	0

Table 4.14 Transect Results of 9C5W Proportion Counting.

	SPECTRAL CLASSES													
	VEGE1		WATER		VEGE2		TWATER		H.D.		L.D.		BS	
LAND USE	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP
U_HDR	0	4	0	0	0	4	4	52	28	84	0	44	0	0
U_LDR	0	0	0	0	0	0	0	0	0	24	68	88	0	20
U_COM	0	0	0	0	0	0	12	68	28	68	0	20	0	0
U_IND	0	0	0	0	0	0	24	40	40	80	0	20	0	16
U_PARK	0	8	0	0	4	44	0	12	0	40	24	76	0	8
U_OPENSP	0	0	0	0	0	0	0	16	0	24	0	44	48	100
U_VEGETA	0	0	0	0	100	100	0	0	0	0	0	0	0	0
U_CWATER	0	0	100	100	0	0	0	0	0	0	0	0	0	0
U_TWATER	0	0	0	84	0	0	16	92	0	0	0	0	0	0

Table 4.15 Transect Results of 15C5W Proportion Counting.

	SPECTRAL CLASSES															
	VEGE1		WATER		VEGE2		TWATER2		TWATER1		L.D.		H.D.		BS	
LAND USE	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP
U_HDR	0	0	0	0	0	4	0	0	4	48	4	52	36	84	0	4
U_LDR	0	0	0	0	0	0	0	0	0	0	56	100	0	8	0	40
U_COM	0	0	0	0	0	0	0	0	12	64	0	32	32	60	0	0
U_IND	0	0	0	0	0	0	0	0	16	36	0	12	44	80	0	32
U_PARK	0	4	0	0	4	44	0	0	0	12	20	80	0	24	0	12
U_OPENSP	0	0	0	0	0	0	0	0	0	16	0	40	0	20	52	100
U_VEGETA	0	0	0	0	100	100	0	0	0	0	0	0	0	0	0	0
U_CWATER	0	0	68	100	0	0	0	4	0	8	0	0	0	0	0	0
U_TWATER	0	0	0	0	0	0	92	100	0	8	0	0	0	0	0	0

Table 4.16 Transect Results of 3C9W Proportion Counting.

	SPECTRAL CLASSES					
	WATER		VEGE		BS	
LAND USE TYPE	LOW	UP	LOW	UP	LOW	UP
U_HDR	7.4	25	34	69	13	44
U_LDR	0	0	17	29	70	80
U_COM	46	51	34	48	3.7	16
U_IND	8.6	32	45	65	8.6	44
U_PARK	1.2	14	30	70	20	67
U_OPENSP	0	29	0	16	61	97
U_VEGETA	0	0	96	100	0	3.7
U_CWATER	100	100	0	0	0	0
U_TWATER	100	100	0	0	0	0

Table 4.17 Transect Results of 9C9W Proportion Counting.

	SPECTRAL CLASSES													
	VEGE1		WATER		VEGE2		TWATER		H.D.		L.D.		BS	
LAND USE	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP
U_HDR	0	1.2	0	0	0	7.4	9.8	29	32	74	2.4	49	0	0
U_LDR	0	0	0	0	0	3.7	0	0	12	17	72	85	0	7.4
U_COM	0	0	0	0	0	0	45	50	39	50	1.2	8.6	0	1.2
U_IND	0	0	0	0	0	0	12	37	44	71	0	24	0	18
U_PARK	0	7.4	0	0	2.4	28	1.2	18	7.4	39	25	54	0	4.9
U_OPENSP	0	0	0	0	0	0	0	30	0	23	4.9	25	33	90
U_VEGETA	0	2.4	0	0	87	100	0	0	0	0	0	9.8	0	0
U_CWATER	0	0	97	100	0	0	0	2.4	0	0	0	0	0	0
U_TWATER	0	0	7.4	65	0	0	32	80	0	0	0	0	0	0

Table 4.18 Transect Results of 15C9W Proportion Counting.

	SPECTRAL CLASSES															
	VEGE1		WATER		VEGE2		TWATER2		TWATER1		L.D.		H.D.		BS	
LAND USE	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP
U_HDR	0	0	0	0	0	6.1	0	0	7.4	27	11	53	32	72	0	2.4
U_LDR	0	0	0	0	0	3.7	0	0	0	0	77	90	1.2	3.7	3.7	16
U_COM	0	0	0	0	0	0	0	0	44	48	2.4	13	39	51	0	1.2
U_IND	0	0	0	0	0	0	0	0	7.4	32	6.1	22	46	67	0	27
U_PARK	0	3.7	0	0	2.4	28	0	0	1.2	14	28	64	9.8	30	1.2	8.6
U_OPENSP	0	0	0	0	0	0	0	0	0	30	3.7	20	0	17	45	96
U_VEGETA	0	1.2	0	0	86	100	0	0	0	0	0	12	0	0	0	0
U_CWATER	0	0	74	97	0	0	0	6.1	2.4	8.6	0	0	0	0	0	0
U_TWATER	0	0	0	0	0	0	97	100	0	2.4	0	0	0	0	0	0

Table 4.19 Transect Results of 3C15W Proportion Counting.

	SPECTRAL CLASSES					
	WATER		VEGE		BS	
LAND USE	LOW	UP	LOW	UP	LOW	UP
U_HDR	4	42	28	50	28	44
U_LDR	0	0	21	28	70	77
U_COM	40	54	36	43	5.3	21
U_IND	11	23	40	58	18	45
U_PARK	4	16	36	56	28	57
U_OPENSP	0	37	0	18	57	88
U_VEGETA	0	0	97	100	0	2.2
U_CWATER	99	100	0	0	0	0.8
U_TWATER	93	100	0	0	0	0

Table 4.20 Transect Results of 9C15W Proportion Counting.

	SPECTRAL CLASSES													
	VEGE1		WATER		VEGE2		TWATER		H.D.		L.D.		BS	
LAND USE	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP
U_HDR	0	0.8	0	0	0	12	4.8	39	27	60	11	51	0.4	2.6
U_LDR	0	0	0	0	2.2	7.5	0	0	10	14	71	82	2.2	5.7
U_COM	0	0	0	0	0	0	41	56	40	44	1.7	11	0	3.5
U_IND	0	0	0	0	0	3.1	12	26	42	63	11	28	0	13
U_PARK	0.4	2.6	0	0	7.1	14	4.4	19	24	37	28	51	1.7	3.5
U_OPENSP	0	0	0	0	0	0	0	37	0.8	24	8.4	28	27	87
U_VEGETA	0	0.8	0	0	91	100	0	0	0	0	0	7.5	0	0
U_CWATER	0	0	97	100	0	0	0	1.7	0	0.4	0	0	0	0
U_TWATER	0	0	25	56	0	0	37	64	0	0	0	0	0	0

Table 4.21 Transect Results of 15C15W Proportion Counting.

	SPECTRAL CLASSES															
	VEGE1		WATER		VEGE2		TWATER2		TWATER1		L.D.		H.D.		BS	
LAND USE	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP	LOW	UP
U_HDR	0	0	0	0	0	10	0	0.4	4	39	19	51	24	52	0.8	9.7
U_LDR	0	0	0	0	1.3	6.2	0	0	0	0	74	88	1.3	3.1	8.4	12
U_COM	0	0	0	0	0	0	0	0	37	51	2.6	12	43	48	0	4.4
U_IND	0	0	0	0	0	2.6	0	0	10	23	16	33	38	59	1.3	20
U_PARK	0	1.3	0	0	7.1	14	0	0	4.4	16	31	55	21	36	4.8	10
U_OPENSP	0	0	0	0	0	0	0	0	0	38	4.8	27	0.8	18	34	91
U_VEGETA	0	0.4	0	0	89	100	0	0	0	0	0	9.7	0	0	0	0.4
U_CWATER	0	0	72	93	0	0	0.4	7.5	6.6	14	0	0	0	0.4	0	0
U_TWATER	0	0	0	0	0	0	90	99	0	7.1	0	0.4	0	0	0	0

The spectral class proportion data extracted from the transects have two characteristics:

(1) From the same land use, the data extracted in this process is different from that extracted from the entire training site. Basically, the data extracted from the transect deviate at a certain distance from the composition results of the training process (refer to Tables 4.9-4.11 and 4.13-4.21).

(2) Different window sizes result in different data. The bigger the window size, the smaller the variation of the proportion data over the space (refer to Figures 4.7, 4.8 and 4.9).

The proportion data is different from the composition data extracted in training process. The major problem is that there are some defects in using window. In the training process, training areas are drawn and the spectral class composition data under each land use type is extracted. There are two important points: (1) the size of the training area is big enough to observe the spectral class characteristics of land use types; (2) the area included in the training area belongs to one land use type only, and it does not include other land use types. These two points, however, cannot be observed when windows are applied. The following examples are used to illustrate the effects of these two points. Different situations resulted from different window sizes are also discussed.

4.3.3 Variation of Spectral Class Proportion Within a Land Use Type

Figures 4.7, 4.8 and 4.9 are the spectral class proportion data extracted from various window sizes along a transect drawn in a *low density residential area*. The X axis is the location of the transect from pixel 228 to 241. The Y axis is the proportion of the spectral classes. These three figures show that the spatial variation of the proportion is the greatest with a 5*5 window size (Figure 4.7). The variation within a 15*15 window (Figure 4.9) is the least.

Each land use type usually consists of different kinds of spectral classes. If the window size is not big enough, the area of proportion counting will be limited. All the spectral classes under a land use type cannot be completely counted. The proportion shown in

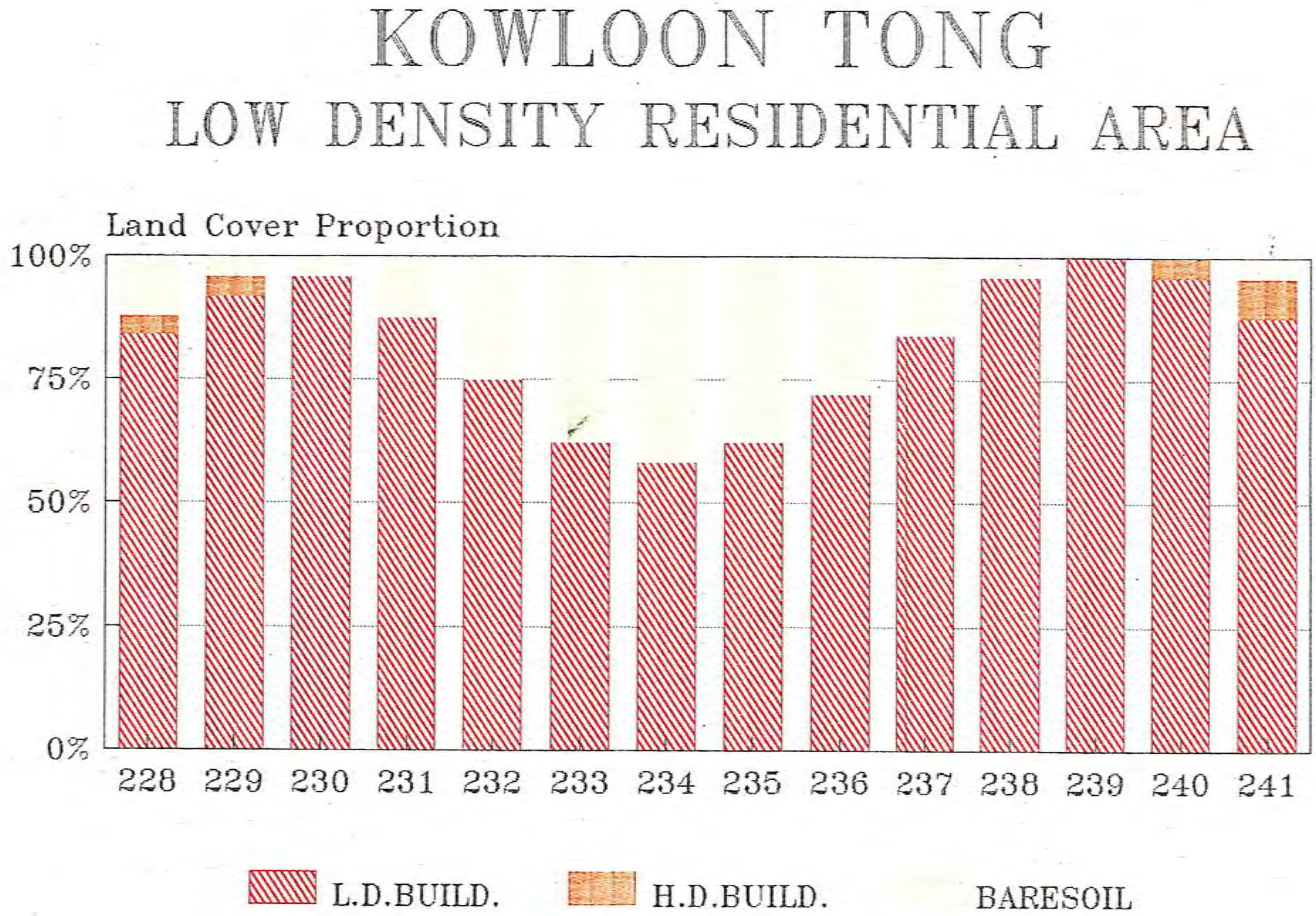


Figure 4.7 The Spatial Variation of the Spectral Class Proportion inside a Land Use Type (15classes 5*5window).

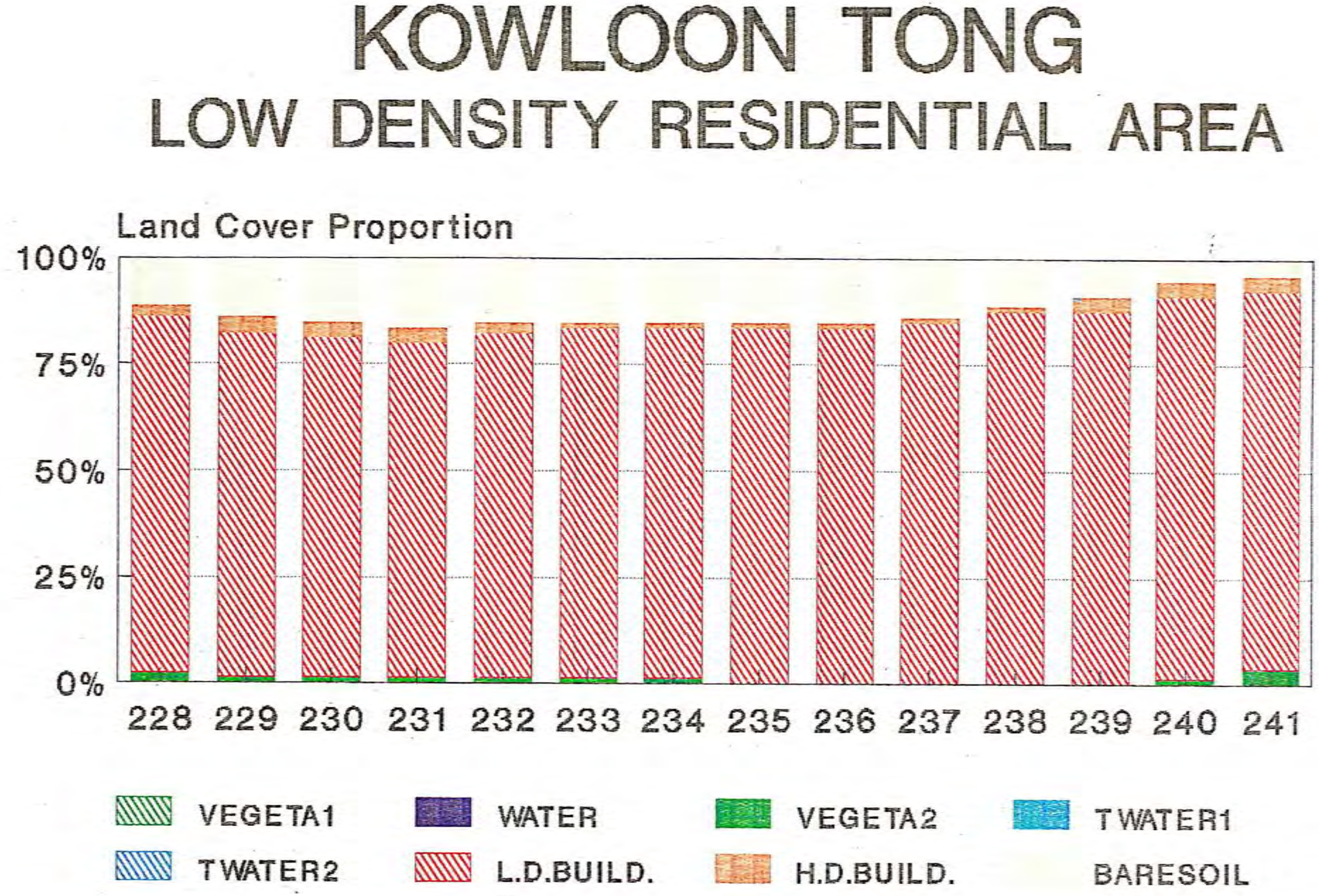


Figure 4.8 The Spatial Variation of the Spectral Class Proportion inside a Land Use Type (15classes 9*9window).

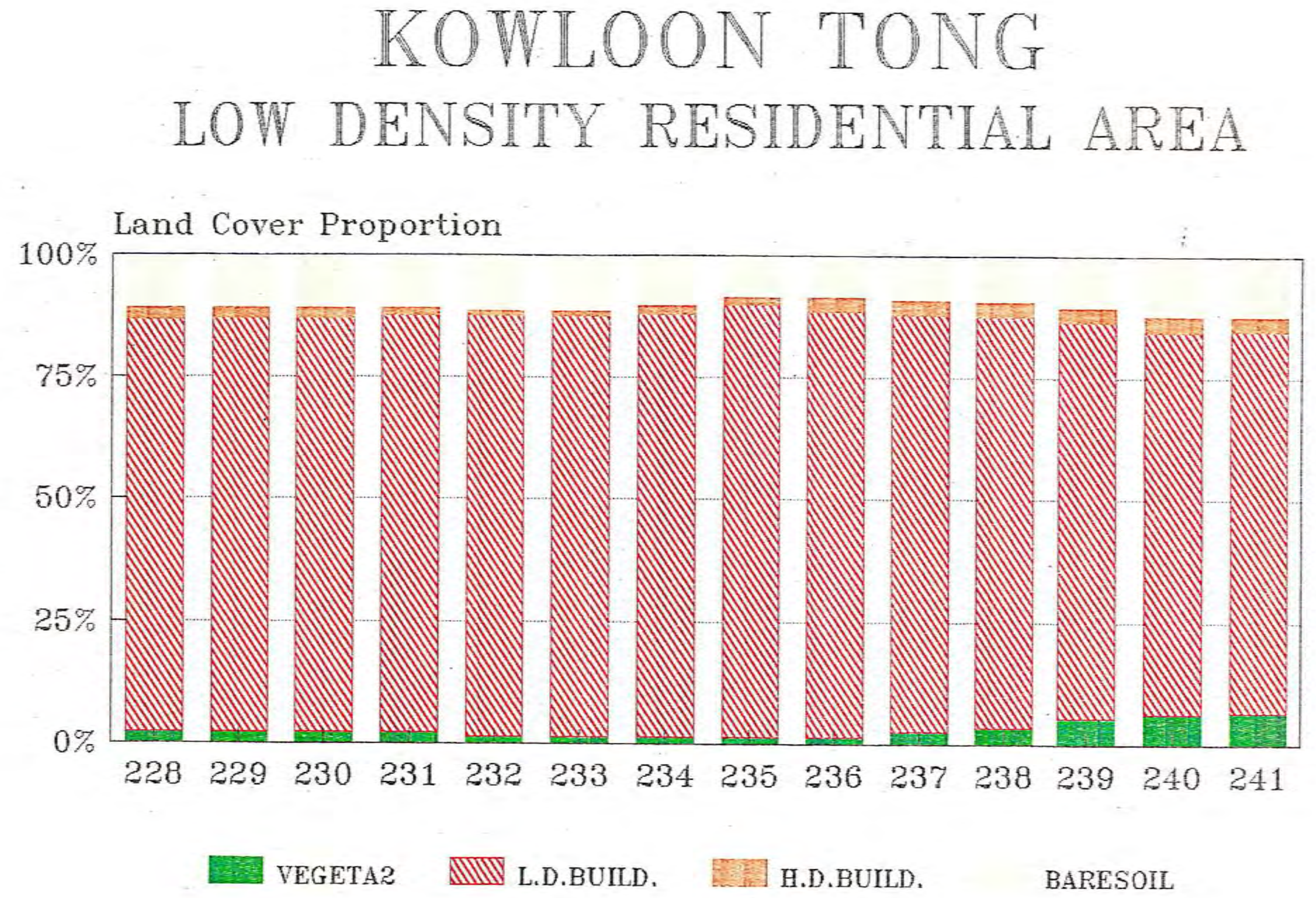


Figure 4.9 The Spatial Variation of the Spectral Class Proportion inside a Land Use Type (15Classes 15*15window).

Figure 4.8 indicates a great variation. It is due to the small window size which bounds the spectral classes within a small area. When the window size is extended to 9*9 and 15*15 (Figures 4.8 and 4.9), it becomes big enough to include the different spectral classes. The variation of the proportion data of a pixel is thus small. The proportion data of *high density residential area* shown in Figures 4.10, 4.11 and 4.12 (with window size of 5*5, 9*9 and 15*15) demonstrate a similar situation. Within a land use type, the smaller the variation of the spectral class proportion, the more accurate we can identify the land use type. As a result, we can conclude that if emphasis is placed on the internal structure of the land use type, the larger the window size, the more accurate the results should be.

4.3.4. Variation of Spectral Class Proportion among Land Use Types

Figures 4.13, 4.14 and 4.15 show the spectral class proportion data extracted from the transect that was drawn across several land use types in an area near Mei Foo. The names of different land use types are listed along the X axis. They include *open space, high density residential area, vegetation* and *industrial area*. Locations with "*" are boundaries while the Y axis is the spectral class proportion.

Similar to as the situation in section 4.3.3, the

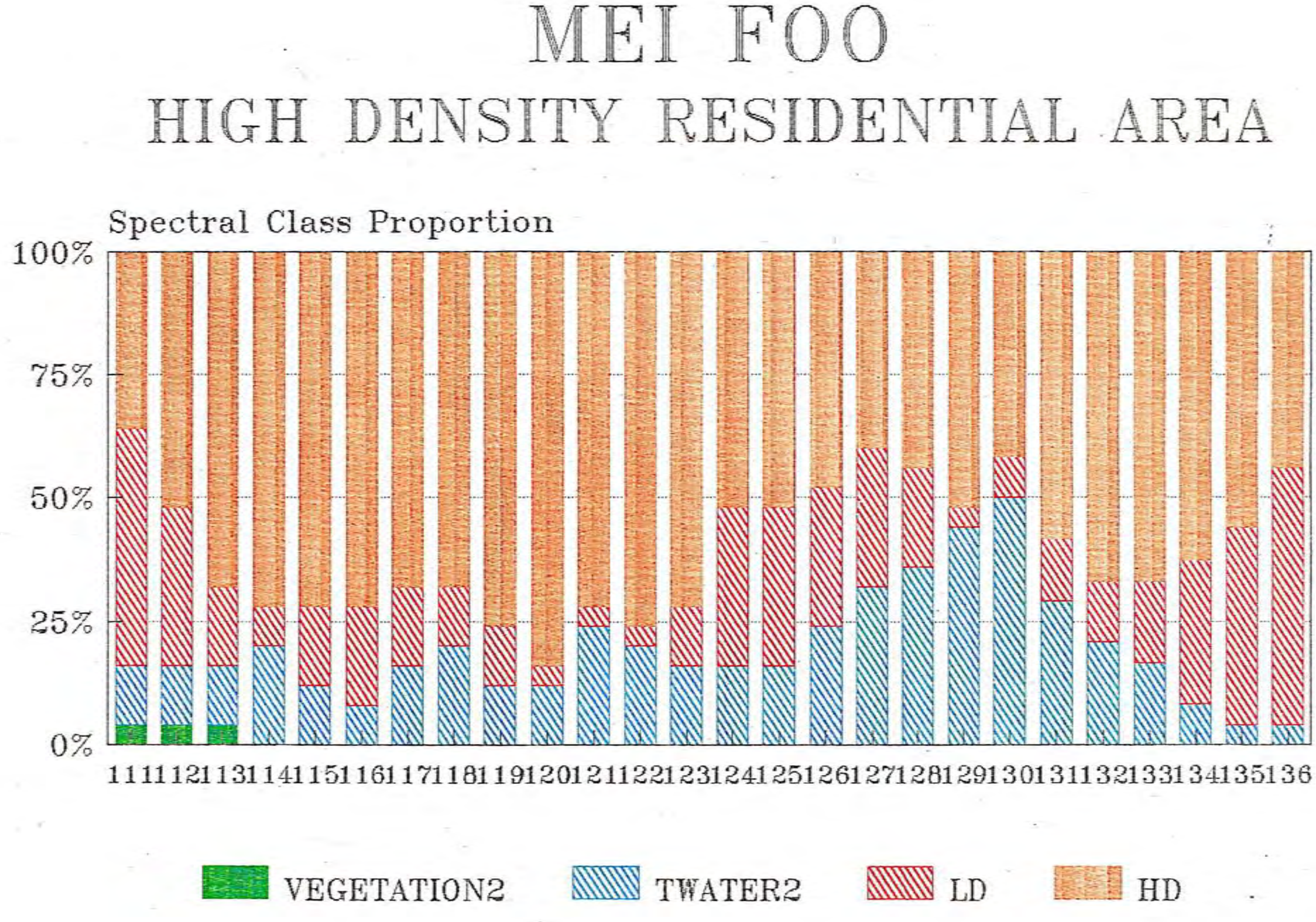


Figure 4.10 The Spatial Variation of the Spectral Class Proportion inside a Land Use Type (15 Classes 5*5 Window).

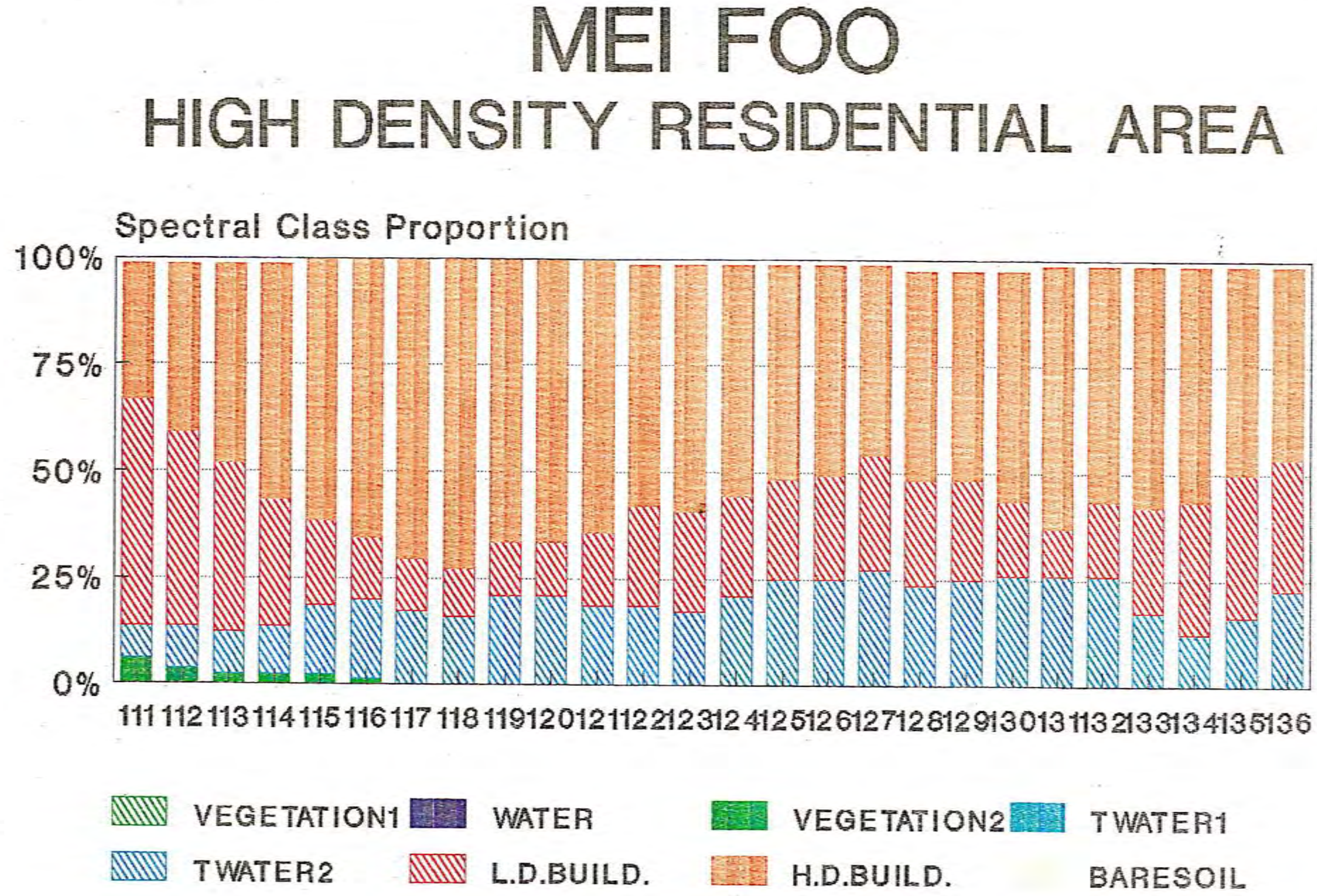


Figure 4.11 The Spatial Variation of the Spectral Class Proportion inside a Land Use Type (15 Classes 9*9 Window).

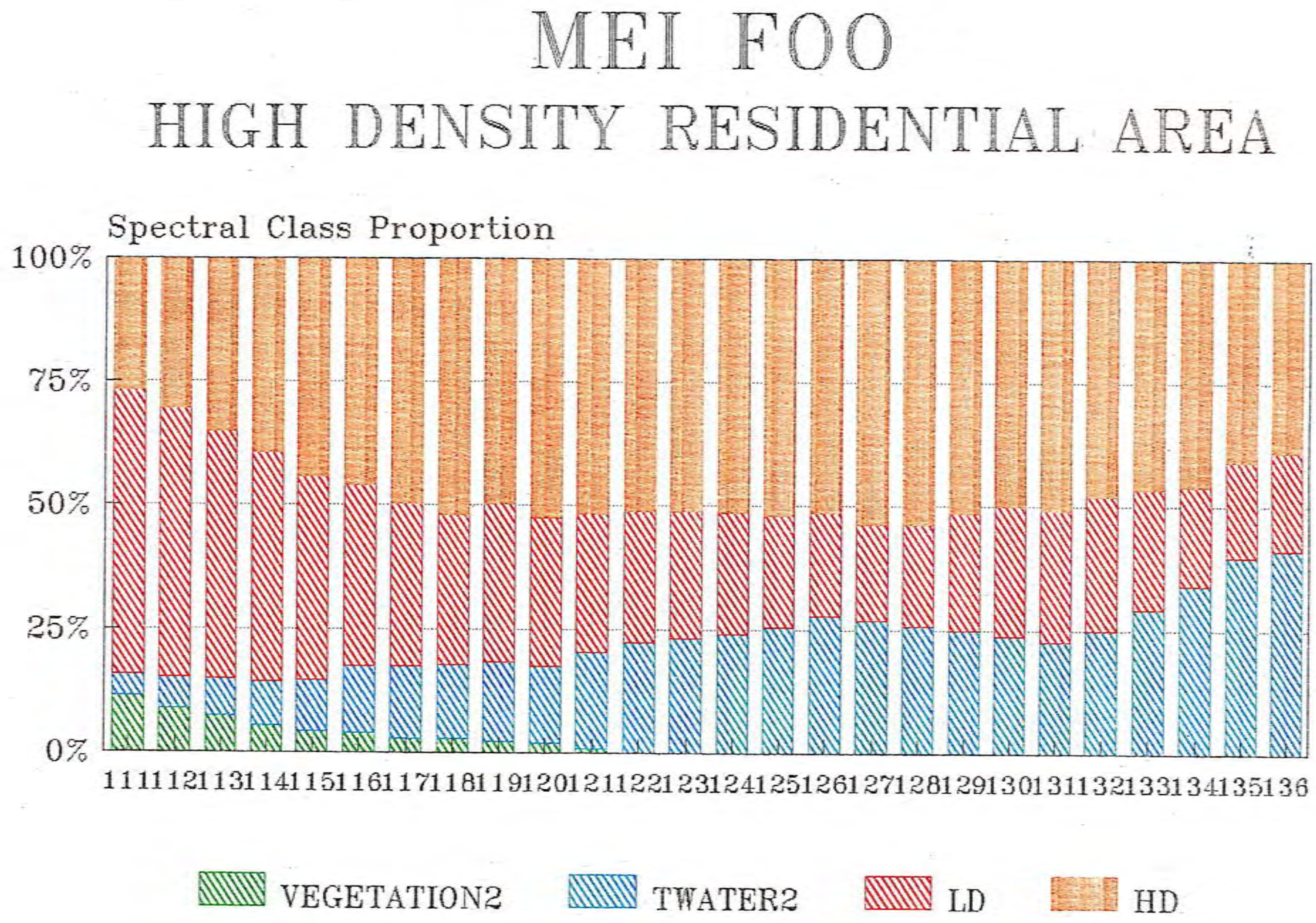


Figure 4.12 The Spatial Variation of the Spectral Class Proportion inside a Land Use Type (15 Classes 15*15 Window).

MEI FOO

BARESOIL, HIGH DENSITY RESIDENTIAL VEGETATION, INDUSTRIAL AREA

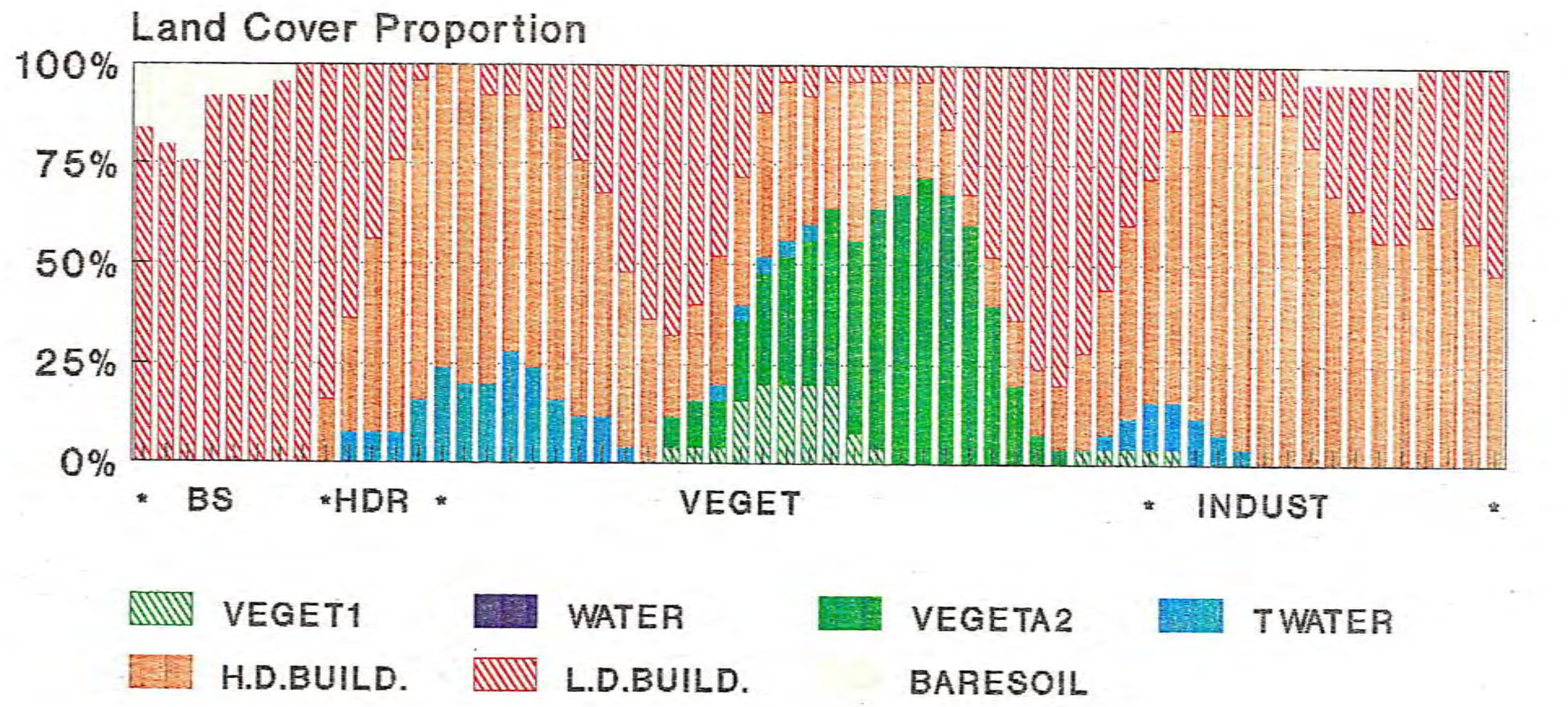


Figure 4.13 The Spatial Variation of the Spectral Class Proportion among Land Use Types (9classes 5*5window).

MEI FOO
BARESOIL, HIGH DENSITY RESIDENTIAL
VEGETATION, INDUSTRIAL AREA

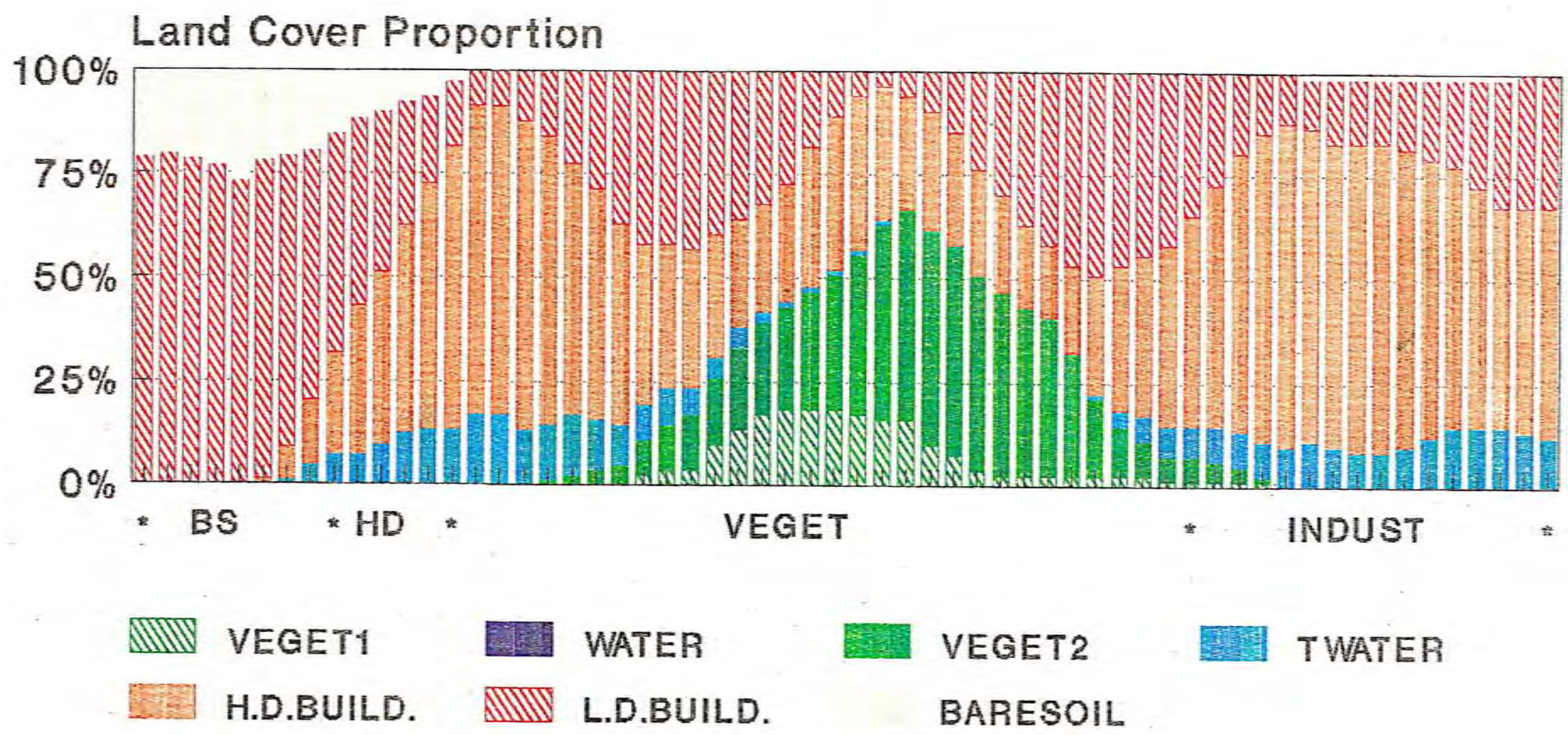


Figure 4.14 The Spatial Variation of the Spectral Class Proportion among Land Use Types (9classes 9*9window).

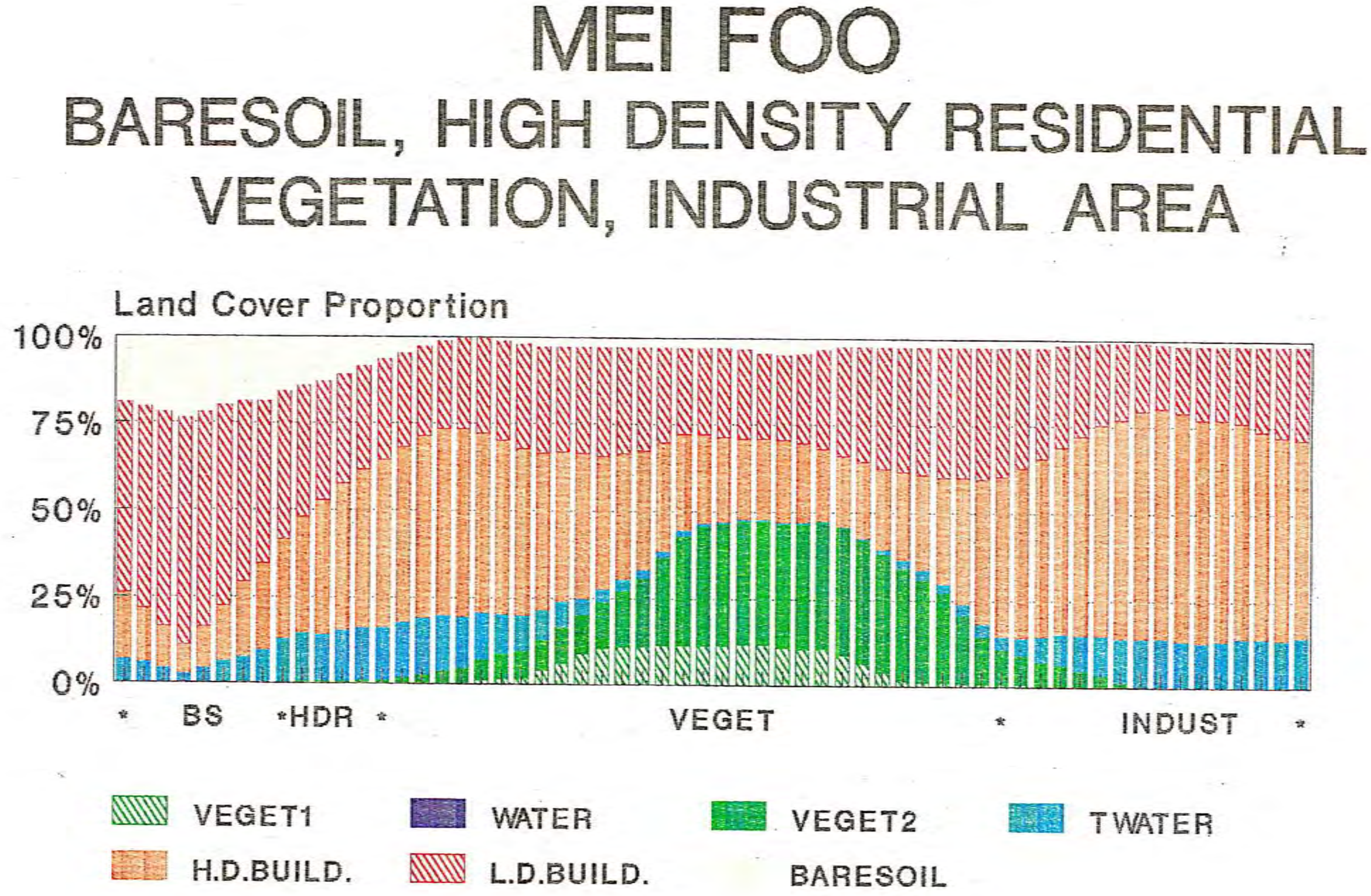


Figure 4.15 The Spatial Variation of the Spectral Class Proportion among Land Use Types (9classes 15*15window).

smaller the window size, the greater is the variation of the proportion. However, in this section, the focal point is not on the internal structure of the land use type but rather the boundary between land use types. The boundary between the land use types can be understood through studying the fluctuations and variations of the spectral class proportion data. This analysis leads to a opposite conclusion on the requirement of the window size. As illustrated in Figure 4.13, the 5*5 window yields a more clear-cut boundary. In Figures 4.14 and 4.15 (especially 4.17), the 9*9 and 15*15 window only lead to smooth fluctuation of the proportion data. This is because with a large window size, the spectral classes in the neighboring land use types are easily included. The boundary between the land use types becomes a transitional area and is difficult to be distinguished. For an accurate delineation of classification, if emphasis is put on the boundary between land use types, a smaller window size will be better.

At this point, it is found that the requirement on the window size is opposite if the focal point is put on the internal structure of the land use types or the boundary between them. In the next chapter, the three window sizes will undergo different experiments to see which one will be more important and applicable in Hong Kong as well as whether a "all-round" window size can be found.

4.4 Summary

Three spectral class maps are derived from the unsupervised classification process. They are 3-class map, 9-class map and 15-class map. After analysis, it is found that the few number of classes in the 3-class map has led to over-generalization. In the 9 and 15-class maps, some classes have few pixels attached and are thus difficult to be matched with the features over the land surface. This problem is more serious in the 15-class map.

In the training process, the spectral class composition of each land use type is extracted. It is found that the results from using 3-class map for extraction are rough. In addition some land use types are found to have similar composition. Whatever it is, the fact that one land use type usually corresponds to more than one spectral classes cannot be ignored.

In the proportion counting process, window algorithm is applied to calculate the spectral class proportion within the surrounding n*n pixels of each pixel on the image. When the proportion data is analyzed by the transect process, it is found that different window sizes result in different variations of proportion data.

CHAPTER 5
RESULTS AND DISCUSSION II — CLASSIFICATION AND ACCURACY ASSESSMENT

This chapter discusses the results of classification and accuracy assessment. There are nine maps resulted from the Spectral Class Composition Method. A resulted map derived from simple per pixel method is also used for comparison. The results of SCCM and simple per pixel method are compared in accordance with the indices of overall accuracy and kappa coefficient. The effects of the number of spectral class and window size on the SCCM are also examined.

5.1 Rule-Based Land Use Classification

5.1.1. Derivation of Rules for Classification

It was noted in Chapter 4 that there were differences between the spectral class composition data extracted in the training process (Tables 4.9 to 4.11) and the (window based) spectral class proportion data extracted from the transect process (Table 4.13-21). Generally speaking, the transect proportion deviates at a certain distance from that of the training data. In selecting rules for classification, this study chooses the upper and lower limits of the spectral class proportion derived from the transect process.

5.1.2 Using Rules for Classification

In Section 4.3.1, nine kinds of proportion counting results are listed out. They are 3C5W[1], 3C9W, 3C15W, 9C5W, 9C9W, 9C15W, 15C5W, 15C9W and 15C15W (Table 4.12). Tables 4.13-21 list out the spectral class proportion characteristics of the various land use types extracted from the transects. These characteristics, same as in the proportion results, are also divided into nine types. One may then ask how these characteristics are used as rules for classifying the proportion counting

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1. For simplicily, C stands for the number of spectral classes and W stands for the window size.

results. The transect result of 3-Class 5*5 Window proportion counting is used as an example to illustrate the process of establishment of the classification rules. Table 5.1 shows the data on the upper and lower limits of the proportion (percentage) (same as Table 4.13). "Up" represents the upper limits while "Low" represents the lower limits. There are 9 land use types that need to be identify. The number of rules that needed to be established is therefore nine.

Table 5.1 The Transect Results of 3C5W Proportion Counting.

	SPECTRAL CLASSES					
	WATER		VEGE		BS	
LAND USE	LOW	UP	LOW	UP	LOW	UP
U_HDR	4	48	36	84	4	56
U_LDR	0	0	0	28	72	96
U_COM	12	68	20	56	4	36
U_IND	20	36	44	80	0	36
U_PARK	0	8	32	92	8	68
U_OPENSP	0	16	0	8	68	100
U_VEGETA	0	0	100	100	0	0
U_CWATER	100	100	0	0	0	0
U_TWATER	100	100	0	0	0	0

Each rule should consider three data (for three spectral classes). They are as follows:

(1) U_H.D.R.:
IF $(4 \leqslant WATER_i \leqslant 48)$ and $(36 \leqslant VEGE_i \leqslant 84)$ and $(4 \leqslant BS_i \leqslant 56)$
then $LU_i \in$ U_H.D.R.

$WATER_i$: The proportion of spectral class WATER at pixel i.
$VEGE_i$: The proportion of spectral class VEGE at pixel i.
BS_i : The proportion of spectral class BS at pixel i.
LU_i : The land use type at pixel i.

(2) U_L.D.R.:

IF ($0 \leqslant WATER_i \leqslant 0$) and ($0 \leqslant VEGE_i \leqslant 28$) and ($72 \leqslant BS_i \leqslant 96$) then $LU_i \in$ U_L.D.R.

(3) U_COM:

IF ($12 \leqslant WATER_i \leqslant 68$) and ($20 \leqslant VEGE_i \leqslant 56$) and ($4 \leqslant BS_i \leqslant 36$) then $LU_i \in$ U_COM

(4) U_IND:

IF ($20 \leqslant WATER_i \leqslant 36$) and ($44 \leqslant VEGE_i \leqslant 80$) and ($0 \leqslant BS_i \leqslant 36$) then $LU_i \in$ U_IND

(5) U_PARK:

IF ($0 \leqslant WATER_i \leqslant 8$) and ($32 \leqslant VEGE_i \leqslant 92$) and ($8 \leqslant BS_i \leqslant 68$) then $LU_i \in$ U_PARK

(6) U_OPENSP:

IF ($0 \leqslant WATER_i \leqslant 16$) and ($0 \leqslant VEGE_i \leqslant 8$) and ($68 \leqslant BS_i \leqslant 100$) then $LU_i \in$ U_OPENSP

(7) U_VEGETA:

IF ($0 \leqslant WATER_i \leqslant 0$) and ($100 \leqslant VEGE_i \leqslant 100$) and ($0 \leqslant BS_i \leqslant 0$) then $LU_i \in$ U_VEGETA

(8) U_CWATER:

IF ($100 \leqslant WATER_i \leqslant 100$) and ($0 \leqslant VEGE_i \leqslant 0$) and ($0 \leqslant BS_i \leqslant 0$) then $LU_i \in$ U_CWATER

(9) U_TWATER:

IF ($100 \leqslant WATER_i \leqslant 100$) and ($0 \leqslant VEGE_i \leqslant 0$) and ($0 \leqslant BS_i \leqslant 0$) then $LU_i \in$ U_TWATER

If LU_i is identified as U_HDR, the value of LU_i will be given as 1. If LU_i is identified as U_LDR, the value of LU_i will be given as 2 and so on and so forth. If LU_i does not belong to any land use types, the value of LU_i will be given as 0. A 0-9 Digital Map is produced according to these rules. If the characteristics of LU_i is suitable for more than one type of rules, the value of LU_i will be given as 12. Each pixel is processed under the nine rules and the whole map of the land use classification results is produced.

5.1.3 Modification of the Rules

As window algorithm is used in proportion counting, spatial variation of the proportion data is resulted. The main reason is that when the window is placed on the boundary and the center of the land use types, the spectral class proportion counted is different. The proportion data from one land use type to neighboring land use type become transitional in nature.

When the upper and lower limits listed in Tables 4.13-4.21 are applied as classification rules, many unclassified pixels are found. It is found that the proportion data in transitional area are outside the limits of the rules. In order to classify them, the rules should be relaxed.

The unclassified pixels ($pixel_i$=0) resulted from the first classification are classified repeatedly. In each classification, the rules is relaxed a little (to extend x% of the upper limits and reduce x% of the lower limits). To avoid overlapping between the land use types, the degree of relaxation should be small. After experiments, a 4% relaxation is considered adequate. In a 5*5 pixels window, 4% is equal to one pixel which is the smallest applicable value. The limits of each rule can thus be enlarged. The pixels near the boundary can then be gradually included in the appropriate land use types. This process is repeated until all unclassified pixels are classified into the appropriate classes.

5.1.4 Classification Results

Figures 5.1 to 5.9 show the rule-based classification results using the Spectral Class Composition Method. Nine classification maps are produced. They are the classification result maps of the 3C5W (3 classes and 5*5 window size), 3C9W, 3C15W, 9C5W, 9C9W, 9C15W, 15C5W, 15C9W and 15C15W respectively. For comparison, Figure 5.10 shows the results of the conventional classification method —— simple per-pixel supervised classification using the spectral reflectance value of the SPOT HRV multi-spectral bands. This serves as a means for finding out the effectiveness of the new method.

An unsupervised classification has been executed. However, under the limitation that there is only sixteen classes produced, the spectral classes derived from the unsupervised method cannot correspond to the classification scheme of this study (Table 3.2). It is particularly difficult to label spectral classes for the *commercial*, *industrial* and *recreational areas*. Supervised classification method, on the contrary, has greater ability in controlling the classification scheme.

The steps of supervised classification are as follows: The analyst attempts to locate specific sites in the remotely sensed data that represent homogeneous examples of these known land use types. These areas are commonly referred to as training sites because the spectral characteristics of these known areas are used to "train" the classification algorithm for eventual land use mapping of the remainder of the image. Multi-variate statistical parameters (means, standard deviation, co-variance matrices, correlation matrices, etc.) are calculated for each training site. Every pixel both within and outside those training sites is then evaluated and assigned to the class of which it has the highest likelihood of being a member. The location of training sites selected are similar to those listed in Table 4.8. The factor of spectral homogeneity is however given special attention in drawing the area. The training areas resulted are thus smaller in size. In the classification process, the maximum likelihood method is used from the PACE/EASI image processing system.

In the classification maps in Figures 5.1 to 5.10, each color represents one land use type (Table 5.2).

Table 5.2 The Legend of Land Use Classification Map.

Class Name	Land Use Types	Color
U_H.D.R.	*High Density Residential Area*	Orange
U_L.D.R.	*Low Density Residential Area*	Yellow
U_COM	*Commercial Area*	Red
U_IND	*Industrial Area*	Purple
U_PARK	*Recreational Area*	Green
U_OPENSP	*Open Space*	White
U_VEGETA	*Vegetation*	Mossy Green
U_CWATER	*Water Bodies*	Blue
U_TWATER	*Turbid Water Bodies*	Light Blue

In order to find out the degree of accuracy of these maps, objective standards should be used. In the following, accuracy of each classification method is assessed to determine its effectiveness.

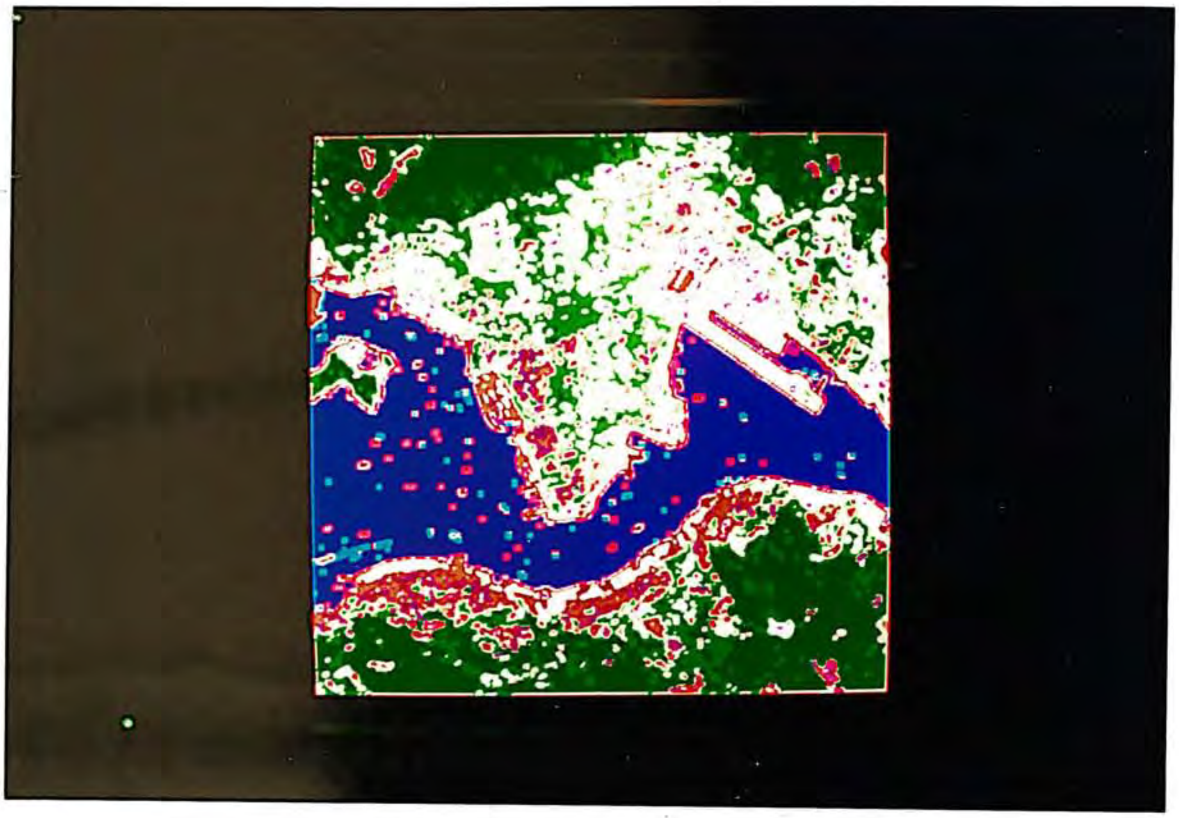

Figure 5.1 3C5W SCCM Result Map.

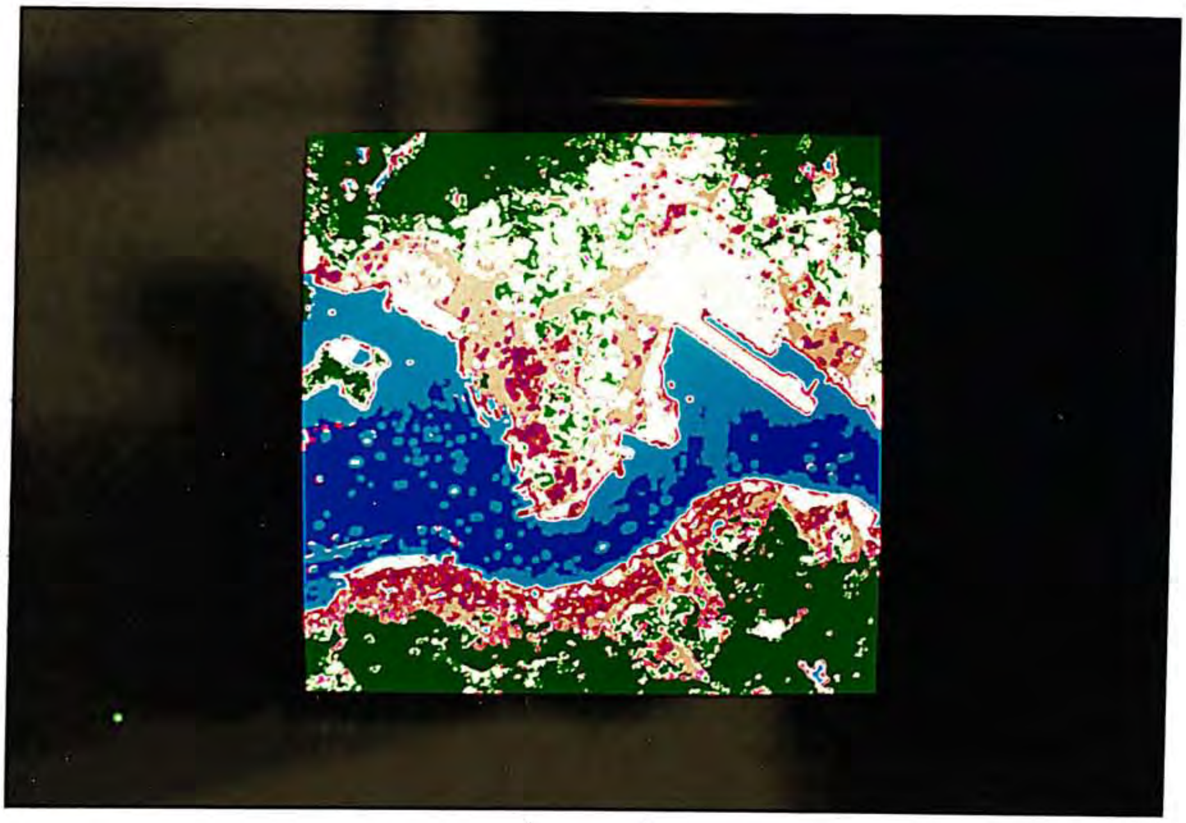

Figure 5.2 3C9W SCCM Result Map.

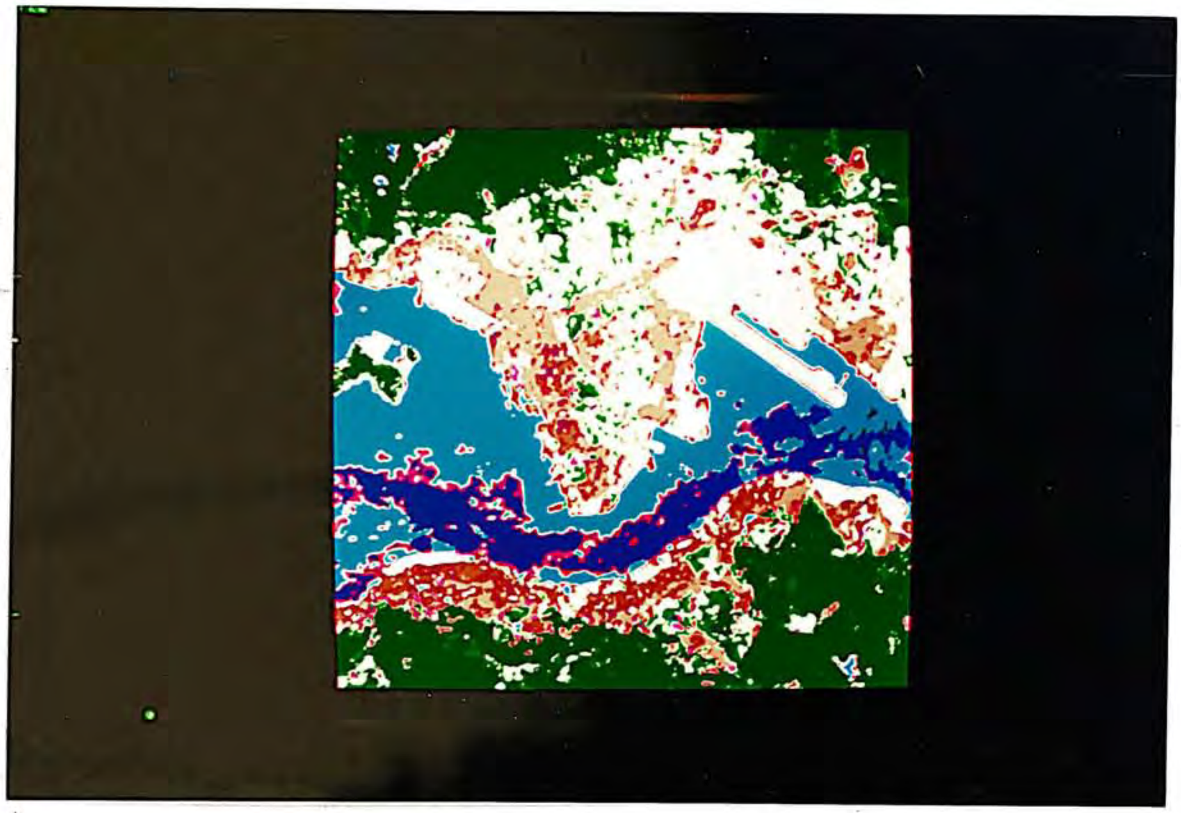

Figure 5.3 3C15W SCCM Result Map.

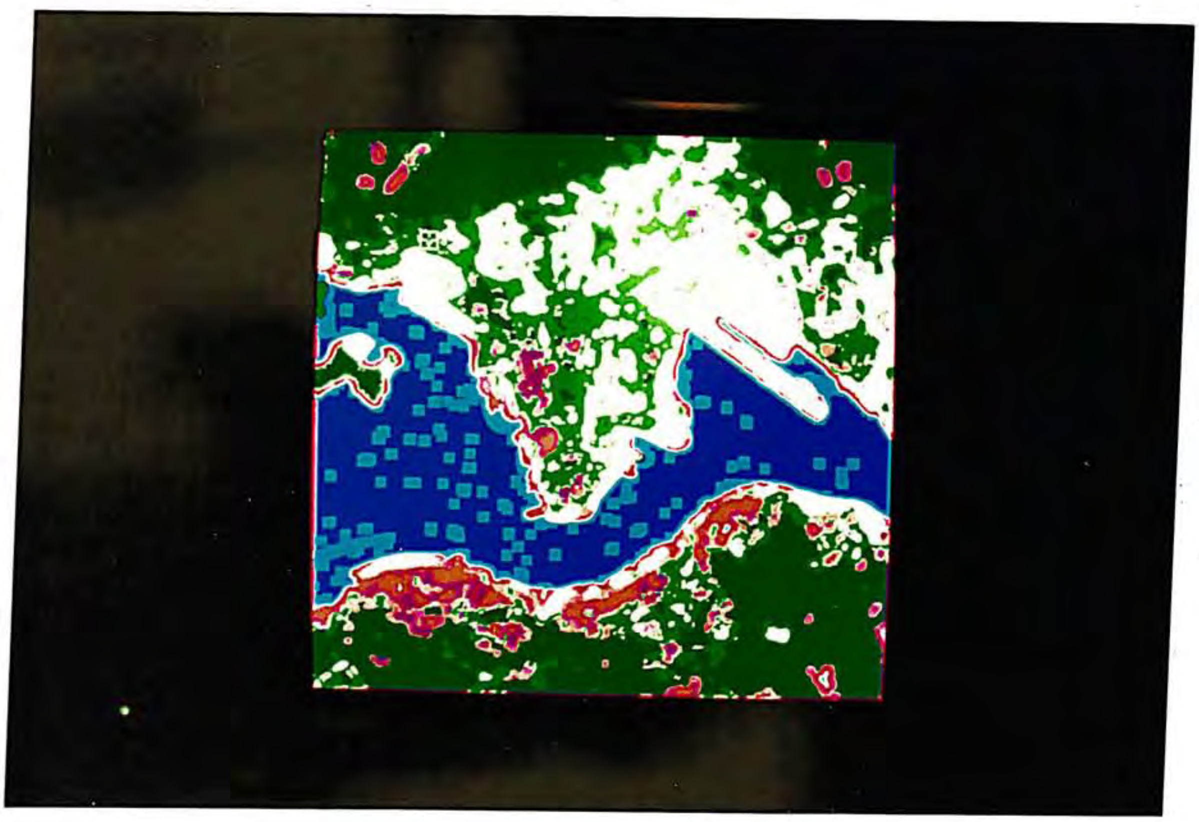

Figure 5.4 9C5W SCCM Result Map.

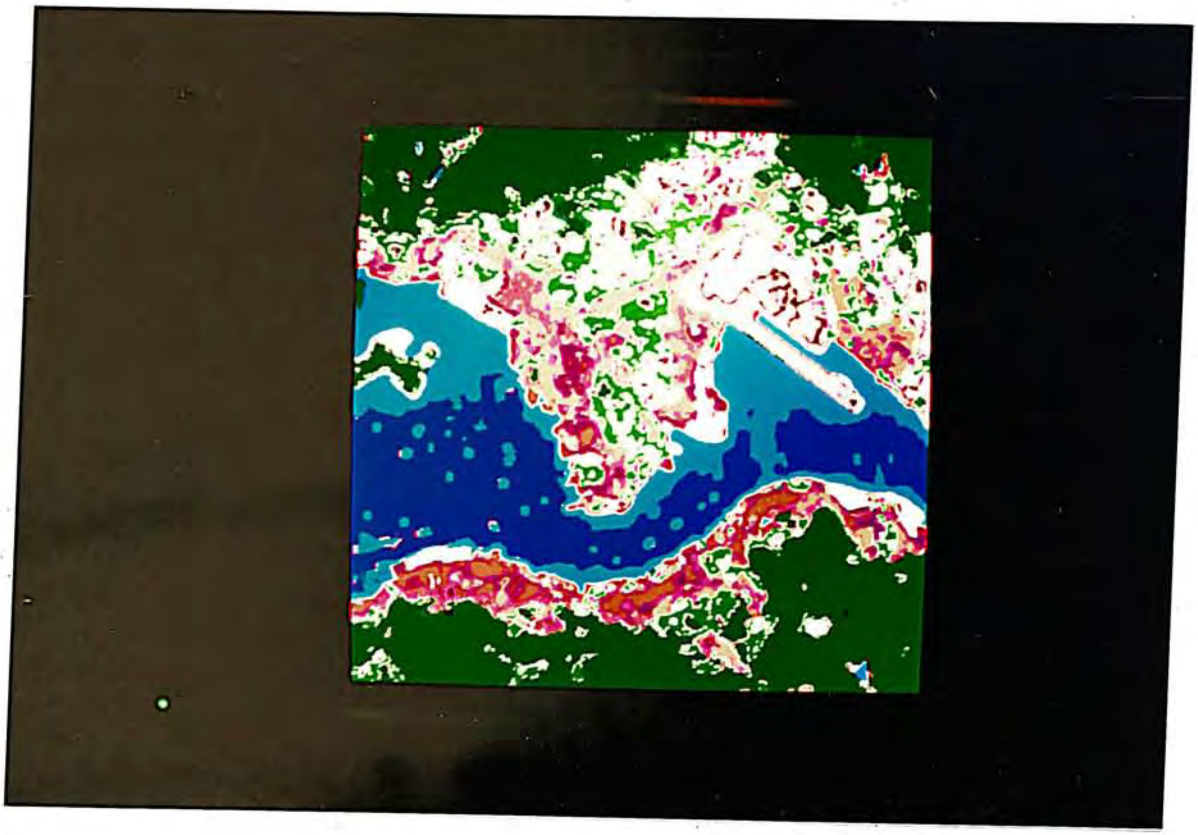

Figure 5.5 9C9W SCCM Result Map.

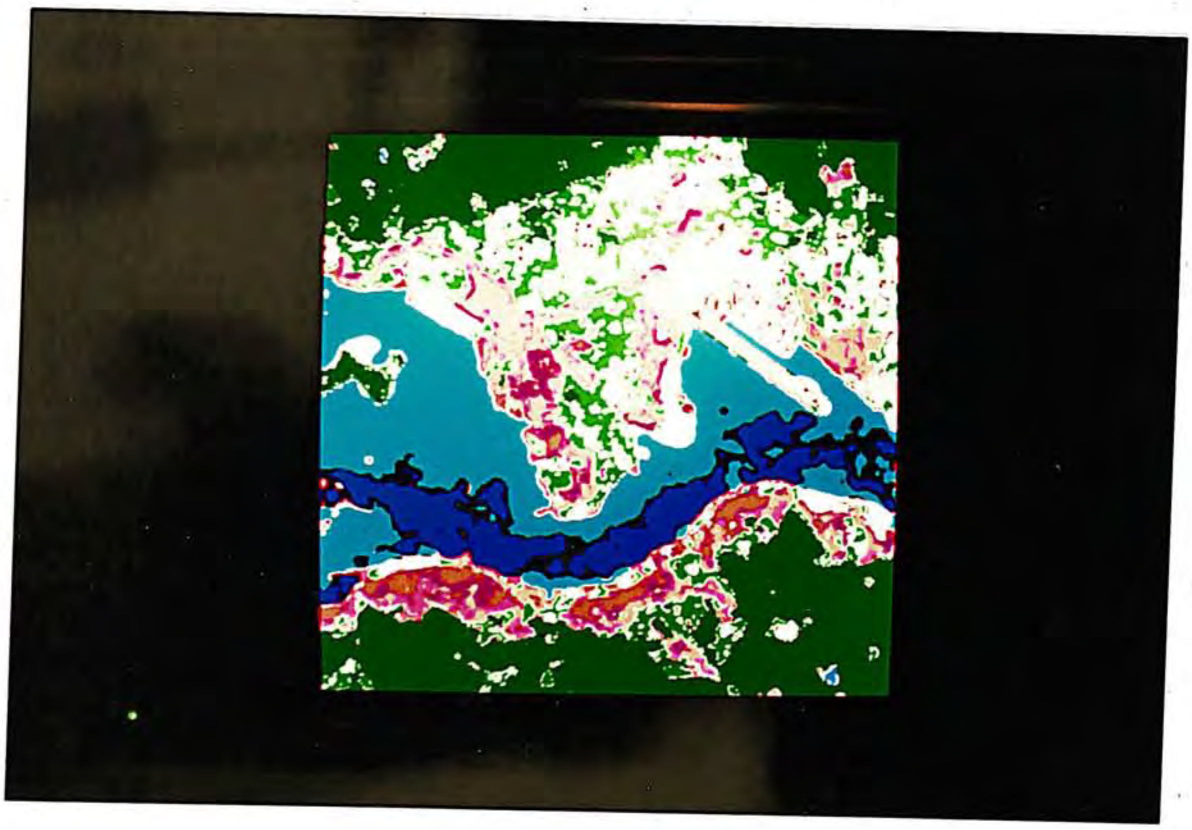

Figure 5.6 9C15W SCCM Result Map.

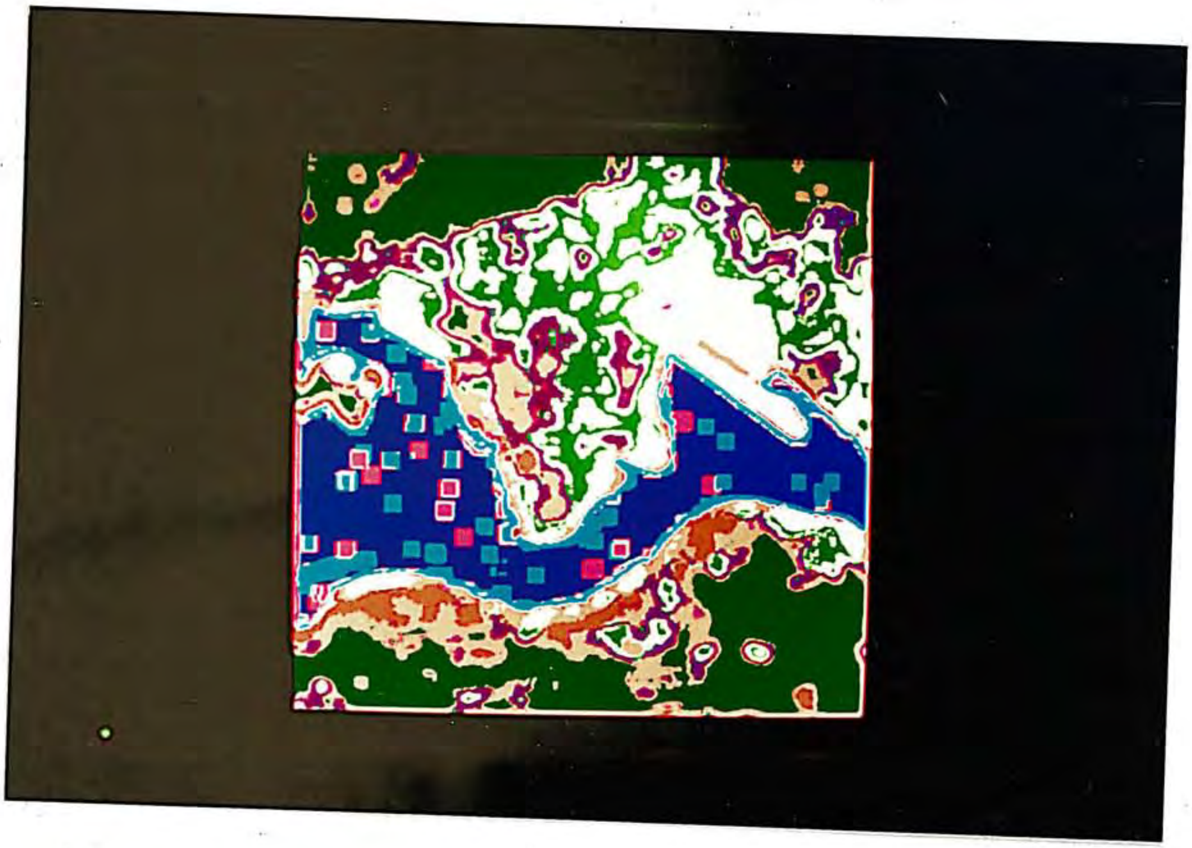

Figure 5.7 15C5W SCCM Result Map.

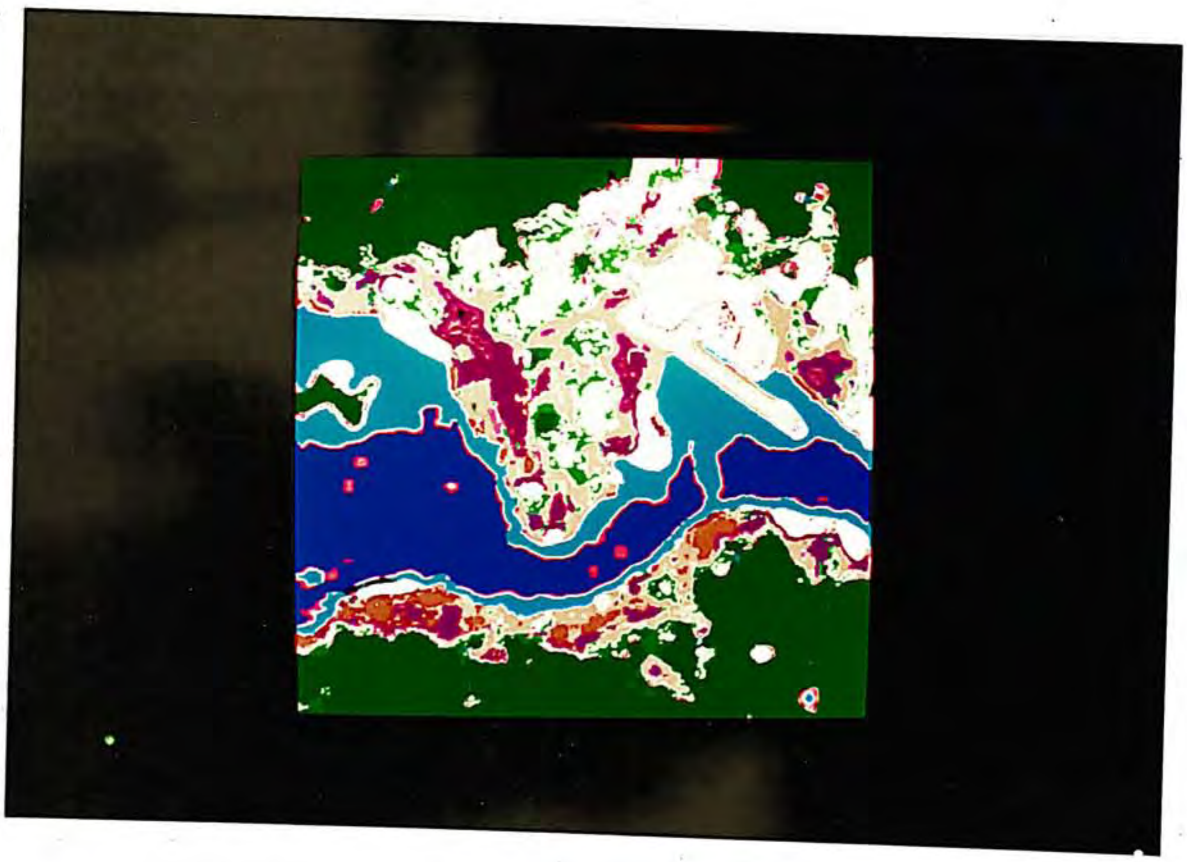

Figure 5.8 15C9W SCCM Result Map.

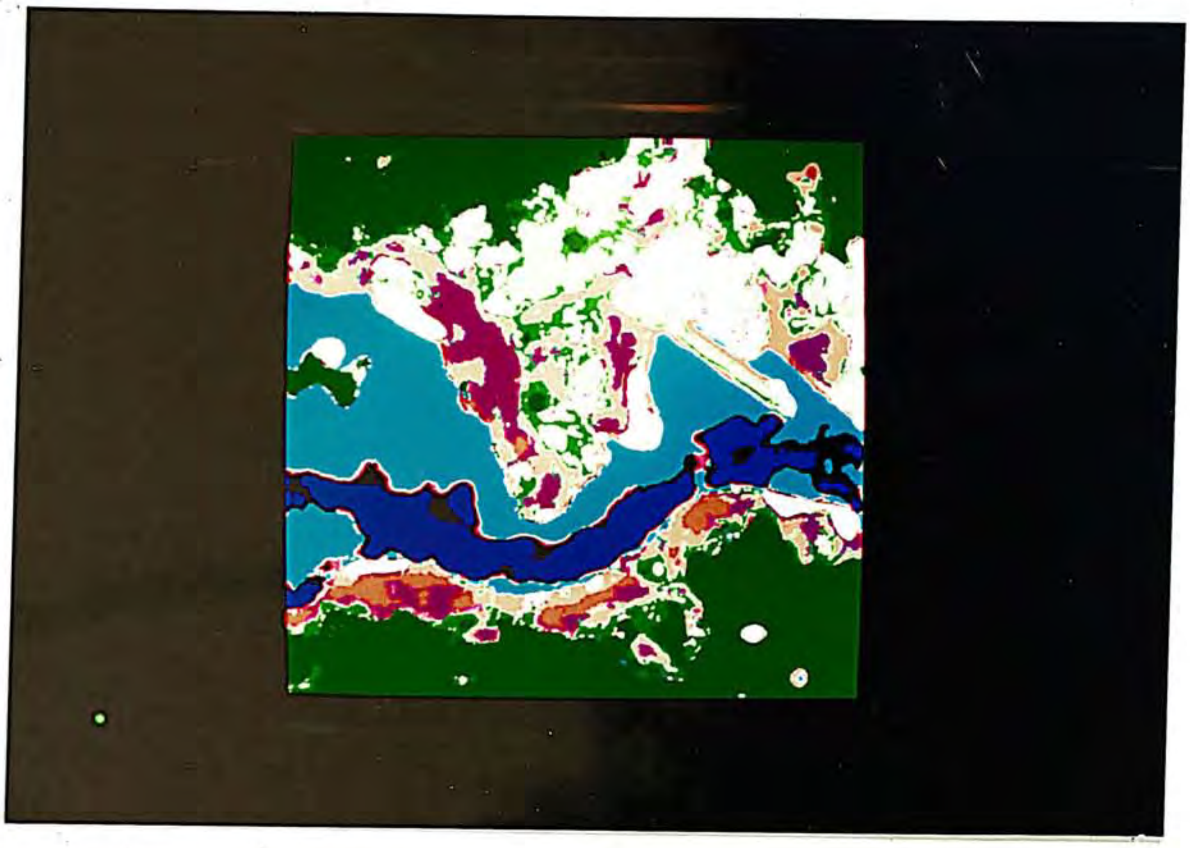

Figure 5.9 15C15W SCCM Result Map.

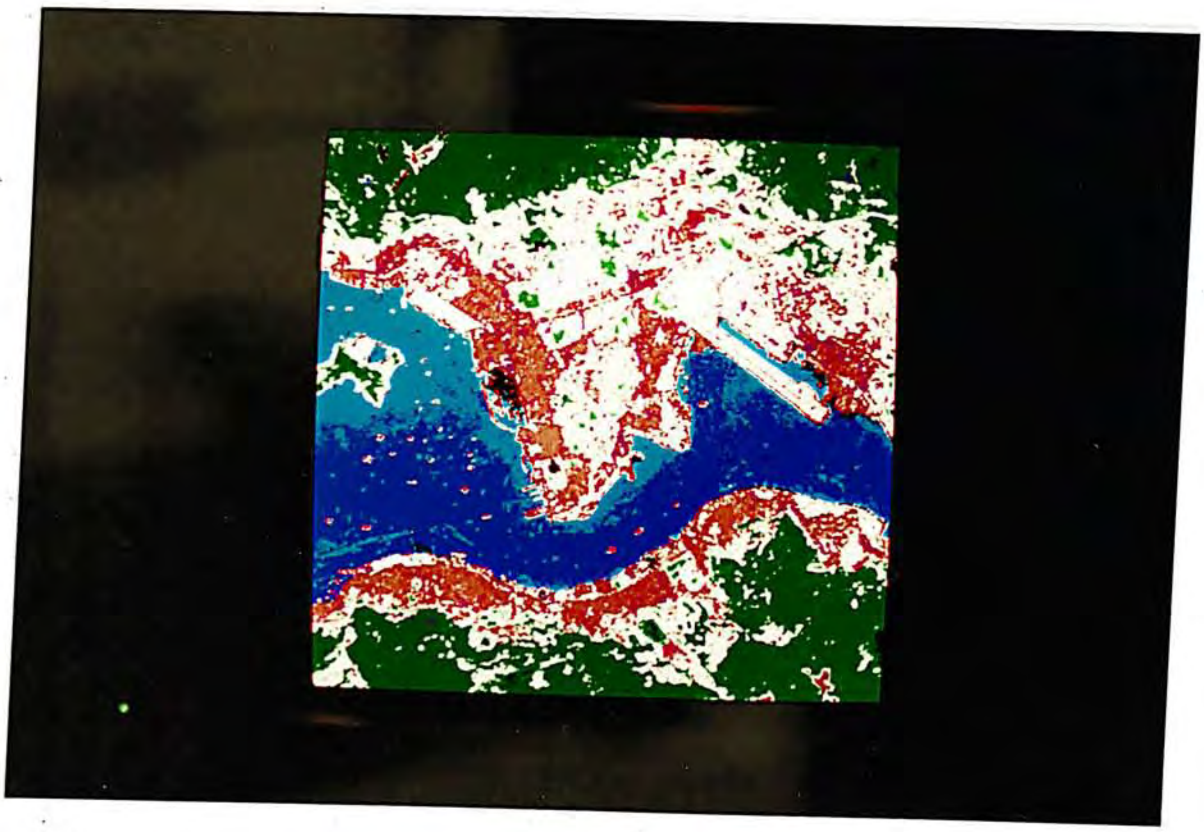

Figure 5.10 Simple Per-pixel Classification Map.

5.2 ACCURACY ASSESSMENT

5.2.1 Accuracy Assessment Process

The steps involved in accuracy assessment was introduced in Chapter 3. According to the 9 types of SCCM and one type of Simple Per-Pixel Classification (SPPC), 10 error matrices are obtained (Tables 5.3-5.12). Based on these error matrices, the overall accuracy (the total number of correctly classified samples divided by the total number of samples) and the kappa coefficient (measure of the actual agreement minus change agreement) of each classification are calculated. These two indices illustrate clearly the degree of accuracy of the classification methods.

Table 5.3 Error Matrix of 3C5W SCCM.

	IMAGE DATA										
	HDR	LDR	COM	IND	PARK	OPENSP	VEGET	CW	TW		
REF. DATA	1	2	3	4	5	6	7	8	9	Pd's Acc.	
1 U_H.D.R.	9	9	6	7	39	5	5	0	0	85	10.59
2 U_L.D.R.	1	3	0	0	13	5	3	0	0	25	12.00
3 U_COM	1	0	4	2	0	1	0	0	0	8	50.00
4 U_IND.	3	2	0	0	4	1	0	0	0	10	.00
5 U_PARK	2	2	2	1	7	3	1	0	0	18	38.89
6 U_OPENSP	1	0	3	0	3	22	0	0	0	31	70.97
7 U_VEGET	4	1	0	1	21	1	74	0	0	102	72.55
8 U_CWATER	0	0	5	1	0	1	0	48	5	62	77.42
9 U_TWATER	0	0	4	0	0	0	0	43	5	58	8.62
Total	21	17	24	12	87	39	83	91	10		
User's Acc.	42.86	17.65	16.67	.00	8.05	56.41	89.16	52.75	50.00		

Overall accuracy: 44.7917
Kappa coefficient: 36.3483
Variance of Kappa: .00082288

Table 5.4 Error Matrix of 3C9W SCCM.

	IMAGE DATA										
	HDR	LDR	COM	IND	PARK	OPENSP	VEGET	CW	TW		
REF. DATA	1	2	3	4	5	6	7	8	9	Pd's Acc.	
1 U_H.D.R.	6	5	8	6	38	4	8	0	0	85	7.06
2 U_L.D.R.	0	6	0	0	10	3	6	0	0	25	24.00
3 U_COM	0	0	4	2	1	1	0	0	0	8	50.00
4 U_IND.	0	1	0	0	6	2	1	0	0	10	.00
5 U_PARK	0	3	0	1	9	3	2	0	0	18	50.00
6 U_OPENSP	2	2	1	0	3	23	0	0	0	31	74.19
7 U_VEGET	2	1	0	1	9	1	87	0	0	102	85.29
8 U_CWATER	1	0	3	0	0	2	0	42	14	62	67.74
9 U_TWATER	0	0	2	0	1	0	0	33	20	58	34.48
Total	11	18	18	10	77	39	104	75	34		
User's Acc.	54.55	33.33	22.22	.00	11.69	58.97	83.65	56.00	58.82		

Overall accuracy: 51.0363
Kappa coefficient: 42.9262
Variance of Kappa: .00080962

Table 5.5 Error Matrix of 3C15W SCCM

	IMAGE DATA										
	HDR	LDR	COM	IND	PARK	OPENSP	VEGET	CW	TW		
REF. DATA	1	2	3	4	5	6	7	8	9	Pd's Acc.	
1 U_H.D.R.	16	8	9	14	21	8	8	0	0	85	18.82
2 U_L.D.R.	2	2	0	4	9	2	6	0	0	25	8.00
3 U_COM	1	0	3	1	1	1	0	0	1	8	37.50
4 U_IND.	1	1	0	3	3	2	0	0	0	10	30.00
5 U_PARK	3	2	0	4	7	1	1	0	0	18	38.89
6 U_OPENSP	4	0	1	1	5	20	0	0	0	31	64.52
7 U_VEGET	5	3	1	6	4	1	81	0	0	102	79.41
8 U_CWATER	5	0	0	1	0	1	0	36	12	62	58.06
9 U_TWATER	5	0	0	0	0	1	0	28	19	58	32.76
Total	42	16	14	34	50	37	96	64	32		
User's Acc.	38.10	12.50	21.43	8.82	14.00	54.05	84.38	56.25	59.38		

Overall accuracy: 48.5714
Kappa coefficient: 39.9225
Variance of Kappa: .00081636

Table 5.6 Error Matrix of 9C5W SCCM

		IMAGE DATA									
	HDR	LDR	COM	IND	PARK	OPENSP	VEGET	CW	TW		
REF. DATA	1	2	3	4	5	6	7	8	9	Pd's Acc.	
1 U_H.D.R.	34	3	4	11	16	1	2	0	2	85	40.00
2 U_L.D.R.	1	7	0	0	11	1	4	0	0	25	28.00
3 U_COM	0	0	2	4	0	0	0	0	1	8	25.00
4 U_IND.	7	0	0	1	0	1	0	0	0	10	10.00
5 U_PARK	1	1	0	1	8	0	2	0	0	18	44.44
6 U_OPENSP	0	2	0	2	6	17	0	0	0	31	54.84
7 U_VEGET	1	1	0	0	13	0	83	0	0	102	81.37
8 U_CWATER	1	0	0	1	1	0	0	42	13	62	67.74
9 U_TWATER	0	0	1	0	0	0	0	15	40	58	68.97
Total	45	14	7	20	55	20	91	57	56		
User,s Acc.	75.56	50.00	28.57	5.00	14.55	85.00	91.21	73.68	71.43		

Overall accuracy: 64.1096
Kappa coefficient: 57.5958
Variance of Kappa: .00081317

Table 5.7 Error Matrix of 9C9W SCCM

		IMAGE DATA									
	HDR	LDR	COM	IND	PARK	OPENSP	VEGET	CW	TW		
REF. DATA	1	2	3	4	5	6	7	8	9	Pd's Acc.	
1 U_H.D.R.	25	2	9	6	20	3	5	0	0	85	29.41
2 U_L.D.R.	2	9	0	0	6	0	6	0	0	25	36.00
3 U_COM	1	0	3	2	0	1	0	0	1	8	37.50
4 U_IND.	6	0	0	1	2	0	0	0	0	10	10.00
5 U_PARK	2	3	0	1	6	0	2	0	0	18	33.33
6 U_OPENSP	1	2	0	1	6	18	0	0	0	31	58.06
7 U_VEGET	0	2	0	0	13	0	86	0	0	102	84.31
8 U_CWATER	0	0	0	0	0	1	0	48	11	62	77.42
9 U_TWATER	0	0	0	0	0	0	1	16	40	58	68.97
Total	37	18	12	11	53	23	100	64	52		
User,s Acc.	67.57	50.00	25.00	9.09	11.32	78.26	86.00	75.00	76.92		

Overall accuracy: 63.7838
Kappa coefficient: 57.0405
Variance of Kappa: .00081359

Table 5.8 Error Matrix of 9C15W SCCM

REF. DATA		HDR 1	LDR 2	COM 3	IND 4	PARK 5	OPENSP 6	VEGET 7	CW 8	TW 9	Pd's Acc.	
		IMAGE DATA										
1	U_H.D.R.	19	1	5	22	21	7	5	0	0	85	22.35
2	U_L.D.R.	2	4	0	0	8	0	11	0	0	25	16.00
3	U_COM	2	0	2	2	0	1	0	0	1	8	25.00
4	U_IND.	2	1	0	3	2	1	0	0	0	10	30.00
5	U_PARK	4	2	0	0	5	2	4	0	0	18	27.78
6	U_OPENSP	5	4	0	1	1	18	1	0	0	31	58.06
7	U_VEGET	0	2	0	0	5	2	92	0	0	102	90.20
8	U_CWATER	1	0	0	0	2	1	1	48	8	62	77.42
9	U_TWATER	3	0	0	0	0	0	0	14	41	58	70.69
Total		38	14	7	28	44	32	114	62	50		
User,s Acc.		50.00	28.57	28.57	10.71	11.36	56.25	80.70	77.42	82.00		

Overall accuracy: 59.6401
Kappa coefficient: 52.1817
Variance of Kappa: .00078942

Table 5.9 Error Matrix of 15C5W SCCM

REF. DATA		HDR 1	LDR 2	COM 3	IND 4	PARK 5	OPENSP 6	VEGET 7	CW 8	TW 9	Pd's Acc.	
		IMAGE DATA										
1	U_H.D.R.	36	9	8	11	15	2	2	0	1	85	42.35
2	U_L.D.R.	1	9	0	0	10	1	4	0	0	25	36.00
3	U_COM	0	0	2	3	0	1	0	0	1	8	25.00
4	U_IND.	7	1	0	1	0	1	0	0	0	10	10.00
5	U_PARK	0	1	1	1	8	4	2	0	1	18	44.44
6	U_OPENSP	1	5	1	0	4	19	0	0	0	31	61.29
7	U_VEGET	1	2	0	0	14	0	85	0	0	102	83.33
8	U_CWATER	0	1	2	0	0	0	1	27	25	62	43.55
9	U_TWATER	0	0	0	0	0	0	0	1	56	58	96.55
Total		46	28	14	16	51	28	94	28	84		
User,s Acc.		78.26	32.14	14.29	6.25	15.69	67.86	90.43	96.43	66.67		

Overall accuracy: 62.4679
Kappa coefficient: 55.9043
Variance of Kappa: .00076278

Table 5.10 Error Matrix of 15C9W SCCM

	IMAGE DATA										
	HDR	LDR	COM	IND	PARK	OPENSP	VEGET	CW	TW		
REF. DATA	1	2	3	4	5	6	7	8	9	Pd's Acc.	
1 U_H.D.R.	27	2	6	6	24	4	3	0	0	85	31.76
2 U_L.D.R.	1	7	0	0	9	1	7	0	0	25	28.00
3 U_COM	1	0	3	2	0	1	0	0	1	8	37.50
4 U_IND.	5	1	0	1	1	1	0	0	0	10	10.00
5 U_PARK	2	1	0	0	8	3	3	0	0	18	44.44
6 U_OPENSP	1	1	0	0	6	20	0	0	0	31	64.52
7 U_VEGET	1	1	0	0	12	1	86	0	0	102	84.31
8 U_CWATER	0	0	0	0	2	1	1	20	25	62	32.26
9 U_TWATER	0	0	0	0	0	0	0	1	52	58	89.66
Total	38	13	9	9	62	32	100	21	78		
User,s Acc.	71.05	53.85	33.33	11.11	12.90	62.50	86.00	95.24	66.67		

Overall accuracy: 61.8785
Kappa coefficient: 54.8388
Variance of Kappa: .00084228

Table 5.11 Error Matrix of 15C15W SCCM

	IMAGE DATA										
	HDR	LDR	COM	IND	PARK	OPENSP	VEGET	CW	TW		
REF. DATA	1	2	3	4	5	6	7	8	9	Pd's Acc.	
1 U_H.D.R.	19	1	6	22	21	8	5	0	0	85	22.35
2 U_L.D.R.	0	7	0	0	6	1	11	0	0	25	28.00
3 U_COM	1	0	2	1	2	0	0	0	1	8	25.00
4 U_IND.	3	1	0	4	1	1	0	0	0	10	40.00
5 U_PARK	2	2	0	1	5	4	4	0	0	18	27.78
6 U_OPENSP	5	2	0	0	2	21	0	0	1	31	67.74
7 U_VEGET	0	2	0	0	9	2	88	0	0	102	86.27
8 U_CWATER	0	0	0	0	1	2	1	23	19	62	37.10
9. U_TWATER	3	0	1	0	0	0	0	2	49	58	84.48
Total	33	15	9	28	47	39	109	25	70		
User,s Acc.	57.58	46.67	22.22	14.29	10.64	53.85	80.73	92.00	70.00		

Overall accuracy: 58.1333
Kappa coefficient: 50.5821
Variance of Kappa: .00083129

Table 5.12 Error Matrix of Simple Per-Pixel Classification

	IMAGE DATA									
	HDR	LDR	COM	IND	PARK	OPENSP	VEGET	CW	TW	
REF. DATA	1	2	3	4	5	6	7	8	9	Pd's Acc.
1 U_H.D.R.	13	24	18	24	2	0	2	0	0	85 15.29
2 U_L.D.R.	1	13	0	1	4	0	6	0	0	25 52.00
3 U_COM	0	0	5	2	0	0	0	0	1	8 62.50
4 U_IND.	1	1	1	6	0	0	0	0	0	10 60.00
5 U_PARK	0	7	1	1	6	0	2	0	0	18 33.33
6 U_OPENSP	2	7	2	5	5	6	1	0	0	31 19.35
7 U_VEGET	0	8	0	0	13	0	81	0	0	102 79.41
8 U_CWATER	1	0	0	0	0	0	1	54	2	62 87.10
9 U_TWATER	1	0	1	0	0	0	0	20	33	58 56.90
Total	19	60	28	39	30	6	93	74	36	
User,s Acc.	68.42	21.67	17.86	15.38	20.00	100.00	87.10	72.97	91.67	

Overall accuracy: 56.3636
Kappa coefficient: 49.5228
Variance of Kappa: .00077962

5.2.2 Analysis of Error Matrices

The following two points can be derived from studying the error matrices:

(1) The classification of several urban land use types including *residential, commercial, industrial and park* usually have much confusion among themselves. Urban land uses are commonly misclassified as park. For example, in the 3C5W SCCM (Table 5.3), over 45% of pixels in the *High Density Residential Area, Low Density Residential Area and Industrial Area* are misclassified as *Park*. In the 3C9W SCCM, over 40% pixels in the urban land use types are also misclassified as *Park*. Other

SCCMS, there is about 70% *Turbid Water* that has been misclassified as *Clear Water*. This is due to the small number of spectral classes in the 3-class SCCM. In the 3 class SCCM, water body alone represents a class after the unsupervised classification. It therefore cannot assist in distinguishing *Clear Water* and *Turbid Water* accurately.

In other SCCMs, findings show that *Clear Water* is usually misclassified as *Turbid Water*. The situation is particularly salient in 15-class SCCM where there is about 50% of error. This may due to the fact that the fact that the ships anchored at Victoria Harbor and the waves caused by the shuttle of ferries and ships have been considered as impurities in the water body. When the window algorithm is used for proportion counting, these "impurities" on the water surface may thus make *Clear Water* to be misclassified as *Turbid Water*.

5.2.3 Comparison Between Spectral Class Composition Method and Simple Per-Pixel Classification

Table 5.13 shows the comparison of the accuracy of the SCCM and the per-pixel method. The method of highest accuracy is placed at the top of the sequence and so on. The indices listed out in the figure are the overall accuracy, kappa coefficient and variance of kappa of the classification methods.

Table 5.14 Accuracy of Each Classification Method.

METHOD	OVER ACC	KAPPA	Var(K)	Z	P
9C5W	64.11	0.575958	0.00081317	2.022812	0.0217
9C9W	63.78	0.570405	0.00081359	1.883425	0.03
15C5W	62.47	0.559043	0.00076278	1.624891	0.0526
15C9W	61.88	0.548388	0.00084228	1.319996	0.0934
9C15W	59.64	0.521817	0.00078942	0.671251	0.2514
15C15W	58.13	0.505821	0.00083129	0.263926	0.3974
PERPIX	56.36	0.495228	0.00077962	0	0.5
3C9W	51.04	0.429262	0.00080962	-1.65472	0.0495
3C15W	48.57	0.399225	0.00081636	-2.40309	0.0082
3C5W	44.79	0.363483	0.00082288	-3.29105	0.0005

In addition, the value difference of the kappa between the SCCM and per-pixel method are further subjected to hypothesis testing to assess the significance of the difference.

Hypothesis:

H_0 is a null hypothesis that there is no difference between SCCM and per-pixel method.
H_1 is a alternative hypothesis that there is a difference between SCCM and per-pixel method.

$$H_0 = KAPPA_i - KAPPA_p = 0$$
$$H_1 = KAPPA_i - KAPPA_p = 0$$

$$Z = \frac{KAPPA_i - KAPPA_p}{[V(KAPPA_i) + V(KAPPA_p)]^{0.5}}$$

$KAPPA_i$: Kappa Coefficient of one of SCCM
$KAPPA_p$: Kappa Coefficient of Per pixel Method
$V(KAPPA_i)$: Variance of the Kappa Coefficient of one of SCCM
$V(KAPPA_p)$: Variance of the Kappa Coefficient of Per Pixel method
Z : Normal Deviation

After Z is calculated, we can check the location of it on the normal distribution curve so that the probability P is found. If P is below the significant level (=0.05) set in this study, the H_0 can be rejected and the difference between the KAPPA of SCCM and SPPC can be proved to be significant.

When only the overall accuracy is taken into account, it is found that the 3 spectral classes SCCM have an overall accuracy lower than that of the simple per-pixel classification. Those of the 9-class and 15-class SCCM are better than that of the per-pixel classification. The results from the 9 classes 5*5 window SCCM has the highest overall accuracy (64.11%). The results of the 9C9W SCCM also has a high overall accuracy of 63.78%. 15C5W and 15C9W are about 62% accurate while 9C15W and 15C15W are 59.64% and 58.13%

accurate respectively. The result of the per-pixel method is 56.36%. In the 3 classes SCCM, the accuracy of 3C9W (51.04%) is not much lower than that of the per-pixel one. The overall accuracy of 3C5W is the least satisfactory (44.79%).

Using kappa coefficient to study the accuracy difference between the different methods, it is found that the results are similar to those of using overall accuracy. Per-pixel method is in the same position (49.52%) in the sequence. The 3-class SCCM has results worse than that of per-pixel method [3C9W (42.93%), 3C15W (48.57%) and 3C5W (44.79%)]. The result of 15C15W is 50.58% while 9C15W is 54.23%. Kappa coefficients of 15C5W and 15C9W are 55.90% and 54.84% respectively. 9C5W (57.6%) and 9C9W (57.04%) have the highest kappa coefficients produced.

Testing the difference of kappa coefficients between SCCM and the per-pixel method, it is found that those of 9C5W ($P = 0.0217 < 0.05$, reject H_0), 9C9W ($P = 0.03 < 0.05$, reject H_0) 3C9W ($P = 0.0495 < 0.05$, reject H_0), 3C15W ($P = 0.0082 < 0.05$, reject H_0), and 3C5W ($P = 0.0005 < 0.05$, reject H_0) have significant differences from the per-pixel method. Other SCCM do not have significant differences from the per-pixel method. This shows that the accuracy of 9C5W and 9C9W SCCM is significantly higher than that of the per-pixel method while 3C9W, 3C15W and 3C5W are significantly lower than the per-pixel method.

In conclusion, the results of SCCM is better than that of SPPC. As pointed out in this study, land use type is usually composed of different types of spectral classes. This point has been verified in Chapter 4. As different land use types consist of different composition of spectral classes, we can in turn use the different spectral classes composition characteristics to identify the land use types. Another important point is that one spectral class can be included in more than one land use type. For example, bare soil exists in the spectral class composition of both the *low density residential area* and *recreational area*. Such situation is not uncommon in the real world

In the simple per-pixel classifier, each pixel is analysed individually. The classification process is only based on the spectral reflectance of each pixel. Land use types are considered to be spectral homogeneous and this makes a land use type usually correspond to one spectral class. Although in some applications of simple per-pixel classifier, especially in the application of unsupervised classifier, one land use can correspond to more than one spectral classes of similar spectral reflectance, it is still different from the concept of "composition of spectral classes". Moreover, in the simple per-pixel classifier, each spectral class is only unrealistically classified into one land use type. Therfore, the actual internal structure of land use type is hidden and error is resulted. As the result, it is reasonable that SCCM, using spectral class composition data to identify land use type can achieve better results.

5.2.4 Discussion on the Results of Producer's and User's Accuracy

To understand the degree of accuracy of different land use types, producer's and user's accuracies are used for analysis.

Figure 5.14 shows all the producer's accuracy of each land use type of each classification. If the best overall accuracy result from the SCCM —— 9C5W —— is used to compare with that of the per-pixel method, it is found that the accuracy of certain land use types in the per-pixel method is higher than those in SCCM. They are *low density residential area, commercial area, industrial area and clear water bodies*. As mentioned in section 4.2.4, the similar building styles in Hong Kong render the spectral class composition of *high density residential area, commercial area and industrial area* similar. Overlappings occur and thus they are classified into inappropriate land use types. On the other hand, the similar composition of *low density residential area and recreational area* has also affected the accuracy.

Table 5.15 Producer's Accuracy of Various Classification Methods.

	9C5W	9C9W	15C5W	15C9W	9C15W	15C15W	PERPIX	3C9W	3C15W	3C5W
U_H.D.R.	40	29.41	42.35	31.76	22.35	22.35	15.29	7.06	18.82	10.59
U_L.D.R.	28	36	36	28	16	28	52	24	8	12
U_COM	25	37.5	25	37.5	25	25	62.5	50	37.5	50
U_IND	10	10	10	10	30	40	60	0	30	0
U_PARK	44.44	33.33	44.44	44.44	27.78	27.78	33.33	50	38.89	38.89
U_OPENSP	54.84	58.06	61.29	64.52	58.06	67.74	19.35	74.19	64.52	70.97
U_VEGETA	81.37	84.31	83.33	84.31	90.2	86.27	79.41	85.29	79.41	72.55
U_CWATER	67.74	77.42	43.55	32.26	77.42	37.1	87.1	67.74	58.06	77.42
U_TWATER	68.97	68.97	96.55	89.66	70.69	84.48	6.9	34.48	32.76	8.62
AVERAGE	46.71	48.33	49.17	46.94	46.39	46.52	46.21	43.64	40.88	37.89

With regard to the land use types of clear water, error is due to the appearance of many ships in the harbour. The clear water bodies with ships is being classified as turbid water bodies in SCCM.

Table 5.15 shows the user's accuracy results. *Open space and turbid water bodies* have higher accuracy with the per-pixel method. However, it should be noted that 80% of *open space* and 40% of *turbid water* have been wrongly classified into other land use types (refer to producer's accuracy). As a result, though the commission error of *open space and turbid water bodies* is low in per-pixel image, a large proportion of the two types has been hidden in other land use types that can not be identified.

Table 5.16 User's Accuracy of Various Classification Methods.

	9C5W	9C9W	15C5W	15C9W	9C15W	15C15W	PERPIX	3C9W	3C15W	3C5W
U_H.D.R.	75.56	67.57	78.26	71.05	50	57.58	68.42	54.55	38.1	42.86
U_L.D.R.	50	50	32.14	53.85	28.57	46.67	21.67	33.33	12.5	17.65
U_COM	28.57	25	14.29	33.33	28.57	22.22	17.86	22.22	21.43	16.67
U_IND	5	9.09	6.25	11.11	10.71	14.29	15.38	0	8.82	0
U_PARK	14.55	11.32	15.69	12.9	11.36	10.64	20	11.69	14	8.05
U_OPENSP	85	78.26	67.86	62.5	56.25	53.85	100	58.97	54.05	56.41
U_VEGETA	91.21	86	90.43	86	80.7	80.73	87.1	83.65	84.38	89.16
U_CWATER	73.68	75	96.43	95.24	77.42	92	72.97	56	56.25	52.75
U_TWATER	71.43	76.92	66.67	66.67	82	70	91.67	58.82	59.38	50
AVERAGE	55	53.24	52	54.74	47.29	49.78	55.01	42.14	38.77	37.06

To examine the accuracy of the different land use types under the different SCCM, 9C5W and 15C5W shows the best results. Most of land use types obtain the highest user's accuracy in 9C5W while producer's accuracy is the highest in 15C5W. It means that the commission error is low when 9 number of spectral class 5*5 window size are used in SCCM and omission error is low when 15 number of spectral class 5*5 window size are used in SCCM.

5.2.5 Discussion on Number of Spectral Class

As shown in Table 5.13, both the overall accuracy and kappa coefficients results show that using 3 spectral classes is inadequate to describe the internal structure of land use types. The differences between the 3 classes SCCM and the 9 and 15 classes are significant. With higher kappa coefficients, the results of 9-class and 15-class SCCM are far better than that of 3 -class.

The difference between the 9 and 15 classes, however, is not great. The main reason is that many classes in the 15-class map have only few pixels attached and are difficult to be defined. The number of spectral classes used for spectral counting in the 9-class and 15-class map is therefore similar. From the accuracy results , we can see that under the same window size, 9 classes usually have better performances. In the 5*5 window SCCM, 9 classes has an overall accuracy of 64.11% while that of 15 classes is 62.47% only. In the 9*9 window size, the overall accuracy of 9 classes is 63.78% and that of 15 classes is 61.88%. In the 15*15 window size, 9 classes is 59.64% accurate which is higher than the 58.13% of the 15 classes. These differences are however far from significant (refer to Table 5.16).

The major difference of 9-class and 15-class map is that the 15-class map has an additional class of very turbid water. Theoretically, more spectral classes may produce clearer internal structure of land use types and achieve higher accuracy in classification. However, there are many spectral classes in the 15-class map that have too few pixels and that their effects on classification are minimal. The additional class of very turbid water in the 15-class map therefore can not increase the accuracy. In the classification scheme, there are only land use types of *clear water bodies and turbid water bodies*. There is no *very turbid water bodies* in the scheme. In the 9-class option, *clear water* *bodies and turbid water bodies* can simply correspond to the spectral class of Cwater (99.8%) and Twater (90.67%). But in the 15-class option, two land use types correspond to three spectral classes and this may lead to the fact that they are more difficult to be classified than in the 9-class option.

Table 5.17 Accuracy of Various Numbers of Spectral Classes.

DIFFERENCE OF	Z	P
3C5W & 9C5W	-5.25302	0
9C5W & 15C5W	0.426089	0.3336
15C5W & 3C5W	-4.91105	0
3C9W & 9C9W	-3.50325	0.0002
9C9W & 15C9W	0.541059	0.2946
15C9W & 3C9W	-2.93099	0.0019
3C15W & 9C15W	-3.05927	0.0011
9C15W & 15C15W	0.397336	0.3446
15C15W & 3C15W	-2.62608	0.0043

On the whole, the 3 classes SCCM cannot clearly reveal the internal structure of the land use types. The 9 classes and 15 classes SCCM have better results while the 9-class are slightly better than the 15-class.

5.2.6 Discussion on Window Size

Another determinant factor in the accuracy is the window size. Neglecting the effects of the number of spectral classes, the overall accuracy is higher if the window size is smaller. Comparing the results derived from the same number of spectral classes, the 5*5 window size SCCM always gives the best result. The 9*9 window size yields the second best while the 15*15 window size gives the worst. As illustrated in the hypothesis testing results in Table 5.17, the difference between 5*5 and 15*15 window size is not significant. The probability is however still close to the significant level. The difference between the 5*5 and 9*9 SCCM results as well as that between the 9*9 and 15*15 results are not large enough to reject the null hypothesis. It can therefore be concluded that the smaller the window size, the better the results of the SCCM will be.

Table 5.18 Accuracy of Various Window Sizes.

DIFFERENCE OF	Z	A	P
9C5W & 9C9W	0.137678	0.0557	0.4443
9C9W & 9C15W	1.213559	0.3869	0.1131
9C5W & 9C15W	1.352430	0.4155	0.0845
15C5W & 15C9W	0.265954	0.1026	0.3974
15C9W & 15C15W	1.040521	0.3508	0.1492
15C5W & 15C15W	1.333022	0.4082	0.0918
3C5W & 3C9W	0.744901	0.2704	0.2296
3C9W & 3C15W	0.882790	0.3106	0.1894
3C5W & 3C15W	1.628023	0.4485	0.0515

In section 4.3, we have already discussed the effects of window size on proportion counting. It is found that small window size is not good for extracting spectral classes structure within land use types but is good for avoiding boundary effect between different land use types. On the contrary, large window size enables a clear observation of the spectral classes within the land use types but difficulties are faced in identifying boundaries between them. The above effects of the window sizes are largely related to the land use characteristics in Hong Kong. Hong Kong has a small area but a dense population. The urban area is highly concentrated. In other words, within a short distance, there are already various land use types. If large window size is used to extract the spectral class composition of the land use types, land use types may easily be mixed with one another. The proportion data is therefore difficult to be identified.

Small window size, on the other hand, is adequate for extracting the spectral class composition within a small land use block and can reduce the chance of the inclusion of other land use types in the counting process. A 5*5 window is thus the best window size in the SCCM.

5.3 Summary

From the transect process, the spectral class proportion characteristics of each land use type are extracted and used as rules for the classification of the entire image. This is called the rule-based classification method.

In accuracy assessment, both the overall accuracy or kappa coefficient show that SCCM has better results than the simple per-pixel method and the 9 classes 5*5 window SCCM has the highest accuracy. The difference between the kappa coefficients of the two methods is also tested and proved to be significant. Moreover, the number of spectral class and the window size have determinant effects on the accuracy of the SCCM.

CHAPTER 6
CONCLUSION

6.1 Summary

Analyzing the results of the training process, It is proved that each land use type is usually composed of more than one type of spectral classes. This is different from the conventional method in which one land use type corresponds to one spectral class.

However, several factors may have determinant effects on the classification results. The number of spectral classes is the first factor. In this study, three kinds of spectral classes are used. They are 3-class, 9-class and 15-class. Three spectral classes tend to over-generalize features on the land surface. To study the internal structure within land use types according to the 3 spectral classes, details cannot be obtained. The 9 and 15 spectral classes show better performance in this aspect. Nevertheless, in the 15-class map, there are many classes that have few pixels attached which makes these classes insignificant in describing the structure of the land use types. The results of 9-class and 15-class maps are therefore similar.

In the training process, we also find that the land use types of high density residential area, low density residential area, commercial area, industrial area and recreational area are spectrally heterogeneous. The other four land use types of open space, vegetation, clear water bodies and turbid water bodies also have heterogeneous characteristics. But, as the number of spectral classes decreases (3 classes), the internal structure of these land use types become homogeneous.

On the other hand, some land use types consist of similar compositions. The spectral class composition data of high density residential area is similar to those of commercial area and industrial area, and the data of low density residential area is similar to that of recreational area. These situations have adverse effects on the classification results.

In the accuracy assessment process, according to the index of overall accuracy, 6 among the 9 types of SCCM show better results than the SPPC (9C5W, 9C9W, 15C5W, 15C9W,9C15W and 15C15W). When the z score is used to test the degree of significant difference of the kappa coefficients between the SCCM and the SPPC, 9C5W and 9C9W have results significantly better than the per-pixel method. 3C15W,3C9W, and 3C5W, on the other hand, are significantly worse than the per-pixel method. The overall testing results show that the SCCM is successfully developed and can produce better results if there is a sufficient number of spectral classes.

Per-pixel method has less satisfactory results since it cannot explore the structural characteristics of the land use types. The so-called scene noise has been viewed as spectral class composition in the SCCM and become the essential features for identifying land use types.

As in the training process, the number of spectral classes also has determining effects on the accuracy of SCCM. The 3 spectral classes are inadequate to describe the land use types' internal structure. 9-class and 15-class are better than 3-class while 9-class is slightly better than 15-class.

Another factor of great importance is the window size. A 5*5 window size is the best. 9*9 is the second best while 15*15 is the worst. This result is closely related to the specific environment in Hong Kong. Hong Kong has a small area but there are about 6 million people dwelling on it. If the window size is too large, characteristics of one land use type will be easily counted into another land use type. The 5*5 window size (100m*100m) is therefore the most appropriate one for Hong Kong.

6.2 Limitations and Problems

From the results of the training process discussed at Chapter 4, it can be easily found that the spectral characteristics of one land use type are largely heterogeneous in nature. The hypothesis that one land use type corresponds to more than one spectral class can therefore be verified. After the classification process, the results of 9C5W and 9C9W SCCM are also proved to be better than that of simple per-pixel classifier when they are subject to the accuracy assessment. Nevertheless, the results are still considered unsatisfactory as the accuracy is lower than 70%. Such a situation is especially salient in the urban land use types of residential, commercial and industrial land.

The following briefly discusses the limitations and problems posed on this study and the factors affecting the classification results of the new method. The first point is the hindrance induced by the software in the unsupervised classification process. The second point focuses on the inadequacies of the window based proportion counting process and the difficulties faced in the selection of the most appropriate window size. The third point explains the effects of the land use characteristics of Hong Kong on remote sensing classification.

(1) Unsupervised Classification Process

When comparing the classification results of the SCCM and the per-pixel method, simple per-pixel supervised classifier is used in this study. Such an application may have some defects. It is because simple per-pixel unsupervised classifier are, generally speaking, more widely used in classifying complex urban land uses. When applying the simple per-pixel unsupervised classifier, many spectral classes (more than 20 and sometimes amount to 100) are obtained. They are then grouped into the appropriate informational classes. Each informational class then correspond to more than one spectral class and the accuracy increases.

As limited by the software, the simple per-pixel unsupervised classifier can only produce 16 types of spectral classes which are insufficient for this study. Therefore, simple per-pixel supervised classifier is used in the selection of targets for comparison. However, it does not mean that the results of SCCM are worse if simple per-pixel unsupervised classifier is used for comparison.

One important process in the SCCM is that the image is divided into several spectral classes through the unsupervised classification process, and then the composition of these spectral classes within each informational class is studied by the training process. This process is in fact similar to the aforesaid simple per-pixel unsupervised method. The major difference between them is that the internal spatial structure of the informational classes has been stressed in the SCCM while simple per-pixel unsupervised classifier pays no attention to it. In the latter classifier, one spectral class can only be grouped into one informational classes (though one informational class can consist of several spectral classes). This is rather irrational. Take one spectral class, baresoil, as an example. It may occur in *low density residential area, high density residential area, recreational area,* and even *industrial or commercial areas.* If each spectral class can only be assigned to one informational class, the real situation is distorted. On the contrary, one spectral class is allowed to occur in more than one informational class in the SCCM. Land use types can be shown more correctly.

As mentioned earlier in Chapter Four, the unsupervised classification process in the SCCM is limited by the software whereby there can only be 16 types of spectral classes. In other words, a large increase in the number of spectral classes can facilitate the study of the internal spatial structure of information classes (ie. the spectral class composition). In view of the above, it is thus believed that if a large increase in the number of spectral class becomes possible in the software used in the unsupervised classification process of the SCCM, the results of the SCCM will still be better than that of direct application of simple per-pixel unsupervised classifier. However, this point have to be proved in the further research.

(2) Window-Based Proportion Counting Process

There are problems in using window algorithm in the proportion counting process. In Chapters 3 and 4, it was discussed that the use of window algorithm in proportion counting leads to a great variation in the spectral class proportion data in one land use type.

In the training process, with reference to other ancillary data, the location and the boundary of one land use type can be clearly found. The spectral class composition obtained from the training site therefore has high representation. Nevertheless, when the window algorithm is applied in proportion counting, whether all pixels belong to one land use type within a window cannot be assumed. Usually, when a pixel is located at the center of a land use type, the representation of the spectral class proportion data derived after the window-based proportion counting is high. On the contrary, when a pixel is located near the boundary, the spectral class proportion of nearby land use types is easily included during the counting process. Errors are thus resulted.

Such problems also affect the extraction of classification rules in the transect process whereby the extent of the rules is often enlarged (since pixels in one nearly land use types are included). In the classification process, overlappings then easily occur between the classification rules of different land use types and errors are resulted.

To prevent these problems, two suggestions are made:

(a) The size of the window has determinant effect on the chance of the occurrence of error. When the window size is big, it straddles the boundary of neighboring land use types and thus the characteristics of these land use types are included. When the size is small, the spectral class proportion characteristics within a land use type cannot be easily studied. Many systematic experiments are therefore required in order to find out the degree of accuracy of different window sizes.

(b) The method can be accompanied by the information of the GIS system. For example, road network can replace window algorithm to be used in proportion counting process. A per-field classification is then conducted. Such a replacement can prevent the spatial variation of the proportion data induced by window based method. The classification accuracy can thus be increased.

(3) Hong Kong has many people but possesses only little flat land. The land use types are unevenly scattered over the land surface. Moreover, the commercial, residential and industrial activities are all situated within high rise buildings in order to make a full utilization of the scarce land. These high rise buildings produce similar spectral reflectance. The results of using SCCM or SPPC are thus affected.

In foreign countries, structure of different urban land uses are more distinctive. For instance, the urban residential area is occupied by houses with gardens. Industrial areas occupying a vast area can consist of oil depots, railway, transportation channels etc. In the central business district there are high rise commercial buildings and apartment buildings. It is comparative obvious that all these land use types are composed of different spectral classes. The new method, SCCM, may therefore be more suitable to be applied in these countries.

6.3 Contribution

The main theme of this study is to introduce a new concept in remote sensing classification . This concept describes the relationship between land use types and spectral classes during the classification process. In common classification methods, spectral characteristics are usually used directly to classify informational class. Though the texture and context of spectral reflectance have received more attention, this study still thought that "composition" should be the most appropriate classification tool. "Composition" means that one information class is correspondent to a composition of spectral classes rather than only one class. SCCM which attempts to identify informational classes by analyzing the composition of spectral classes is established.

In the training process, it is clearly seen that the composition can assist in understanding the structural characteristics of land use types. It is also proved that one land use type is composed of more than one spectral class.

In the accuracy assessment, SCCM shows better results than the simple per-pixel method. The accuracy however is still unsatisfactory. It is due to the small amount of class number in the unsupervised classification process, inaccuracy induced by window algorithm, insufficiency of the classification rules and the actual land use characteristics in Hong Kong. The SCCM therefore still possesses a lot of inadequacies and its procedures are incomplete. Whatever it is, this study is hoped to initiate a starting point to apply spectral class composition in understanding the internal structure of land use types. Further studies on the concept are therefore required.

6.4 Further Research

The discussion on the limitations and problems of this study has in fact briefly outlined the further points that are worth studied. Among them, the first point is how to eliminate the limitation of small spectral class number in the unsupervised classification process induced by the software. Methods should be developed to obtain more spectral class with a view to understand more and clearer the internal structure of land use types. Another step is to replace the window algorithm by road network (input from GIS) in extracting proportion data along the boundaries. Per-field classification will be further made. This could reduce the spatial variation induced by using window algorithm in proportion counting. It is believed that SCCM can produce more satisfactory results if the above improvements are made.

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